Earnings, Marriage, and the Variance of Family Income by Age, Gender, and Cohort*

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Abstract

For birth cohorts 1935–44, 1945–62, and 1964–74, we estimate the contribution of education; permanent heterogeneity in wage rates, employment, and hours; labor market shocks; spouse characteristics and shocks; nonlabor income shocks; and marital histories to the age profiles of the variance of family income per adult equivalent. Education and employment heterogeneity are key sources of the rise in the variance with age and across cohorts. Wage heterogeneity is important at all ages. Own characteristics and shocks matter more for men than women, while spouse characteristics and shocks matter more for women. Gender differences have declined across cohorts.

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1 Introduction

We address two questions that are key to understanding the distribution of family income. First, what are the sources of inequality in family income at different points in the lifecycle? Second, what are the mechanisms through which they influence inequality? Quantifying the sources of inequality requires a model of how the distribution of earnings is shaped by factors such as education, permanent heterogeneity in wages and employment, and shocks to wages and hours. But to study *family income*, one must additionally consider marriage and divorce, as well as marital sorting on characteristics that matter for earnings and marital stability. Consider, for example, education. Education influences the distribution of own earnings through wage rates, employment, and hours conditional on employment. But education also influences family income by affecting marriage formation and stability and by influencing the earnings potential of a person's marriage partner.

Previous research points to labor supply, job mobility, stochastic wage and employment shocks, education, and unobserved heterogeneity in wage rates as contributors to the age profile of the variance of earnings.[1] Because the roles of men and women in the labor market differ, the earnings processes and the determinants of the family income distribution are likely to differ by gender, with spousal earnings playing a more important role for women. By the same token, shifts across birth cohorts in gender roles will change the sources of inequality. Goldin (2006, 2021), Lundberg and Pollak (2007), Ruggles (2015), Blau and Winkler (2017) and other scholars have shown that married women's labor force participation has grown significantly, while male participation rates have moderately declined. Women's educational attainment has surged compared to men's, narrowing the wage gap between genders. As a result women now contribute a larger share of family earnings than they did previously. Concurrently, declines in marriage and fertility rates have reduced the importance of gender disparities within marriage in labor market participation. These factors point to the importance of considering gender and birth cohort when studying the age profile of the distribution of family income.

In this paper, we decompose the variance in annual family income and earnings by age, gender, and birth cohort into various sources. The decompositions are based upon Altonji, Giraldo-Páez, Hynsjö, and Vidangos' (2024; henceforth AGHV) statistical model of earnings, marriage, marital sorting, fertility, and nonlabor income. The equations of the model depend upon gender, and key parameters vary with birth year. AGHV estimate their model using data from the Panel Study of

[1] For a recent survey, see Altonji, Hynjsö, and Vidangos (2023). The Global Repository of Income Dynamics Project (https://www.grid-database.org/) provides micro statistics on income inequality and income dynamics for 13 countries and a number of recent research papers. See Guvenen, Pistaferri, and Violante (2022) for an overview of the project and McKinney, Abowd, and Janicki (2022) for evidence for the US.

Income Dynamics (PSID) for the years 1969 to 2018. For the 1935-44, 1945-62 and 1964-74 birth cohorts, AGHV use the model to provide gender- and cohort-specific estimates of how various shocks affect the mean path of future earnings and family income. They also use the model to decompose the variance of total earnings and total family income obtained between the ages of 25 and 50 into the contribution of an individual's permanent characteristics and shocks, spouse characteristics and shocks, and marital history.

In contrast to AGHV, in this paper we focus on the *age profile* of the variances of annual earnings and family income rather than on lifetime totals. More specifically, we use the model to assess the sources of inequality by age, as well as by gender and cohort, in the logs of individual earnings and family income per adult equivalent. (We often refer to the latter as y_ae_{it}, where i and t are person and year subscripts.)[2] We consider an "early" cohort (individuals born between 1935 and 1944, inclusive), the baby boom cohort (1945 to 1962) and a "later" cohort (1964 to 1974).[3] We decompose the contribution to the variance in family income per adult equivalent at six different ages: 26, 30, 35, 40, 45, and 50. The variance components we consider are education; three permanent unobserved heterogeneity components affecting wage rates, employment status, and hours worked given employment; employment shocks, wage shocks, and hours shocks; random variation in spouse's education and permanent characteristics; spouse's wage shocks; nonlabor income shocks; and random variation in marital status over a lifetime.[4]

To keep the presentation of results manageable, we proceed in two stages. In the first, we abstract from cohort differences and focus on the average across cohorts of the age profiles of the variance contributions. Then we consider changes across cohorts. Our results are based on variances estimated using simulated data from the model.

We find that, on average across cohorts, the variance of y_ae_{it} increases from 0.46 at age 26 to 0.62 at age 50 for men and from 0.59 to 0.69 for women. Education and the permanent component of employment (the random effect in a dynamic multinomial logit model of labor force status) are key contributors to the rise in $var(y\_ae_{it})$ with age. The contribution of the permanent component of the wage is also large, especially for men. But it decreases with age for men and it increases slightly for women. Permanent heterogeneity in annual work hours (conditional on positive hours)

[2] We use adult equivalents rather than person household count to account for returns to scale in a household and children's lower use of resources. We use the OECD's adult equivalence scale.

[3] We chose to end the last cohort at 1974 so that at least half of the cohort had reached age 50 by 2018, the last year of PSID data that we use. This reduces the amount of out-of-sample simulation at older ages for the later cohort. We stop at age 50 for the same reason.

[4] Because our model is not utility-based and is not structural, we cannot explore changes in the distribution of welfare. Nor do we distinguish between anticipated and unanticipated variation. We are not aware of a structural analysis of earnings, marriage and divorce, fertility, and marital sorting that could be used for this purpose, but papers with some of the necessary elements include Keane and Wolpin (2010), Eckstein, Keane, and Lifshitz (2019), and Low et al (2020).

plays only a minor role. The variance contributions of autoregressive and i.i.d. wage shocks and hours shocks are also substantial, especially for men, but have offsetting effects on the age slope of the y_ae_{it} variance. Employment shocks are important for men and increase modestly with age. Nonlabor income shocks contribute moderately to the increase in the variance of y_ae_{it} with age, especially for women.

Because men account for a larger share of family earnings, random variation in spouse characteristics, particularly education and the permanent employment component, contribute more to the variance of family income for women, and the contribution rises with age. The variance contributions of the random variation in the spouse's permanent wage and in the spouse's wage shocks are also larger for women but have a flat age profile. The contribution of random variation in marital history to the family income variance rises with age for women, but is smaller and follows a U-shaped pattern for men.[5]

How do the variance profiles and decompositions differ across birth cohorts? For both genders, the simulated data show a dramatic increase across cohorts in both the level and the age slope of the variance of family income. Most of the shift occurs between the baby boom cohort and the later cohort.

For the early cohort of women, the variance profile of y_ae_{it} is relatively flat at around 0.6. For the later cohort, the variance rises from 0.60 at age 26 to 0.83 at age 50. For women, the variance of earnings (averaged across all ages) decreases by a modest amount between the early and baby boom cohorts, but increases from 1.74 to 1.89 between the baby boom and the later cohort. The age profile of the variance is also steeper in the later cohort. That cohort saw the variance rise from 1.4 at age 26 to 2.2 at age 50.

For men, the age profile of the variance of y_ae_{it} is almost flat for the early cohort and averages around 0.50 across all ages. The baby boom average is similar, but the age profile is steeper. As was the case for women, the variances are much higher and steeper for the more recent cohort. They average about 0.64 and rise from 0.46 at age 26 to 0.76 at age 50. The earnings variance profiles also shift up and become steeper across cohorts.

We find some important changes across cohorts in the contributions of the various sources of income variance. First, because women in the later cohort are more permanently attached to the labor market throughout their lives, the contribution of the permanent wage component is larger at all ages compared to the earlier cohorts, reducing gender differences.

Second, the level and slope of the variance contribution of the permanent employment component

[5]Note that due to data limitations, our definition of "marriage" includes both legal marriage and cohabitation for more than 1 year.

increased substantially across cohorts. For men, the average contribution across all ages increased from about 0.027 to 0.109 between the early and late cohorts. For women, the increase is from 0.020 to 0.075. As we discuss below, the employment random effect (which has a mean of zero and a variance that depends on gender but not on age or cohort) becomes more important as employment probabilities for men decline from high levels, placing more of them on the margin of working. For women, the growing importance of permanent employment heterogeneity is due to large increases in the wage rates and annual hours of women who work. The increases made employment heterogeneity more consequential for the variance of earnings.

Third, for both genders the age profiles of the variance contribution of education are more similar for the early and later cohorts but, to our surprise, lie above and are steeper than the profiles for the baby boomers.

Fourth, the importance of random variation in the spouse's permanent characteristics (including education) and in the spouse's wage shocks has changed very little or slightly declined across cohorts for women, while rising for men relative to women. These changes reflect partial convergence in the labor market behavior of married men and women.

Fifth, the contribution of marital history to the variance of y_ae_{it} has risen for women and declined on net for men. The mechanisms are hard to briefly summarize here but are discussed in the paper

Sixth, we measure the extent to which marital sorting on education, the permanent wage component, and time-varying wage components increase inequality. We find that sorting increases the income variance by about 7% for women in the early cohort but matters very little for women in the later cohorts or for men.

Our paper, like AGHV, builds on several literatures. We have already mentioned the literature on long-term changes in female labor supply, wages, fertility, and marriage. We also draw on the extensive literature on marriage, divorce, and marital sorting.[6] Eckstein, Keane, and Lifshitz (2019) use a parsimonious structural model to study differences between the 1935 and 1975 birth cohorts in employment, wages, education, marriage pattern, and fertility. Also relevant to our research are papers examining the link between assortative mating and trends in inequality, including Fernández and Rogerson (2001), Fernández, Guner, and Knowles (2005), Hyrshko, Juhn, and McCue (2017), Chiappori, Salanie, and Weiss (2017), and Chiappori et al (2020). Our model and analysis is more descriptive, but considers sorting on a more complete set of factors and allows assortative mating

[6] Browning, Chiappori, and Weiss (2014) survey the literature on marriage and sorting in an environment where search costs are low. Papers with search include Moffitt and Rendall (1995), Keane and Wolpin (2010), and Goussé, Jacquemet, and Robin (2017).

to change over time and across cohorts. We quantify the importance of sorting and of random variation in various spouse characteristics for the distribution of family income by age, gender, and cohort.

The model that we use relates to a vast literature on work hours, wages, and earnings. Some studies focus on the effects of wages, marriage, and children on labor supply. Others consider determinants of wages. Papers on the wage elasticity include Blau and Kahn (2007), who study change over time. Juhn and McCue (2016) consider the marriage gap in earnings for women. The rapidly growing literature on the effects of children on employment, hours, and wages includes recent papers by Angelov et al. (2016), Kleven et al. (2019), and Andresen and Nix (2022). Blau and Kahn (2017) survey the literature on gender differences in labor market outcomes and provide references to studies of the effects of marriage and children on work and wages, as well as the effects of workforce interruptions. A separate literature studies the consequences of unemployment shocks for future wages and employment.[7] The equations of our earnings model draw loosely on this vast literature but do not advance it. The contribution of this paper, building on AGHV, is to pull together the components into a dynamic model of lifetime earnings and family income for both men and women and use it to study the sources of inequality by age, gender, and birth cohort.

Finally, we also contribute to the literature on change over time and/or change with age in the cross-sectional variance of wage rates, earnings, and, in a few cases, family income. Particularly relevant studies here are Blundell, Graber, and Mogstad (2015) and Blundell et al. (2018), which considers the role of marital sorting and the effects of the tax and transfer system. Our multivariate analysis complements the many papers that have used univariate processes for earnings and/or family income to study the dispersion and volatility of earnings.[8]

The paper continues in Section 2 with a discussion of the data. Section 3 summarizes the model from AGHV, with additional details relegated to Appendix B. In section 4, we use regressions based on simulated data from the model to provide information on how the effects of education, the permanent heterogeneity components, and spouse characteristics on family income and earnings vary with age and birth cohort. Section 5 reports decompositions of the variance of outcomes over

[7] See Jacobson, Lalonde, and Sullivan (1993) and Davis and von Wachter (2011), among others.

[8] Contributions include Gottschalk and Moffitt (1994), Moffitt and Gottschalk (1995), Moffitt and Gottschalk (2011), DeBacker et al. (2013), Hu, Moffitt, and Sasaki (2019), and Ziliak, Hokayem, and Bollinger (2022). A growing theme of the univariate literature is the importance of considering nonlinear models and non-normal error processes, as demonstrated by Geweke and Keane (2000) and more recently by Arellano, Blundell, and Bonhomme (2017), De Nardi et al. (2021), and Guvenen et al (2021). Our multivariate model is consistent with nonnormality and nonlinearity in log earnings even though most of the errors are normal. Other papers that use multivariate models of earnings dynamics include Altonji, Smith, and Vidangos (2013), Card and Hyslop (2021), and structural papers by Low, Meghir, and Pistaferri (2010) and Heathcote, Storesletten, and Violante (2014). See Altonji, Hynsjö, and Vidangos (2023) for an overview of the multivariate and univariate literatures on earnings dynamics with detailed references.

the lifecycle into several sources. Section 6 concludes.

2 Data

We use the same data as AGHV. It is a panel of American heads of household and their spouses from 1969 to 2018 taken from the SRC sample of the PSID. To estimate the model, we typically restrict to the heads and spouses who are sample members and between the ages of 25 and 61 and born in 1935 or later. We exclude Black sample members.[9] We begin the sample at age 25 because many of the questions that we need to analyze earnings, family income, and family composition are only asked for heads of household, and many sample members under the age of 25 are not yet heads of household. We exclude sample members over the age of 61 or those with potential experience higher than 40 because we do not model retirement decisions.

2.1 Definitions of Main Variables

Our variable definitions and choices are influenced by data availability. The PSID switched from an annual to a biennial interview starting in 1997, but some questions are now asked both for the previous calendar year and for the calendar year before last. This allows us to create an annual panel past 1997. For many of the variables, we impute data when it was missing. For a complete accounting of sample selection, data cleaning, and data imputation procedures, see Appendix A.[10] We use capital letters to indicate a variable is in levels and lower case letters to indicate a variable is in logs. We converted all monetary variables to 2012 dollars using the personal consumption expenditures implicit price deflator.

Hours. $HOURS_{it}^{*}$. Hours are annual hours worked in all jobs in the calendar year. We set hours to a minimum of 200 when we use the variable in estimation. We also apply a ceiling of 4000. This variable comes from a question about the year prior to the survey and, in odd years after the survey switched to being biennial, a two-year retrospective question. The "*" on the hours variable (and wages below) highlights the fact that in estimation we treat them as measured with error.

Hourly Wage Rate. $WAGE_{it}^{*}$. We define the wage as annual earnings divided by hours (before hours are set to a minimum of 200 but after they are set to the maximum of 4000). We impute wage rates when they are missing, either because earnings are not available or hours are zero. The imputation makes use of either a separate PSID question regarding the wage rate at the survey date, if it is available, or using demographic variables if it is not.

[9] In ongoing work, we are studying differences in family income dynamics by race.

[10] Appendix Tables A.1a–A.1c display summary statistics for the PSID sample.

Earnings. $EARN_{it}$. This is annual earnings in all jobs in the calendar year. Like $HOURS$, this variable is constructed using both one-year and two-year retrospective questions. We impose a floor of \$1300 prior to taking logs but after creating the wage measure. We do not subsequently adjust PSID earnings to reflect the application of the wage floor. As a result, $ln(EARN_{it})$ is sometimes below the sum of the logs of our PSID wage and hours measures.[11] Note that $EARN_{it}$ is only used to evaluate fit. It does not play a direct role in estimation of the model or in the variance decompositions.

Employment Status. E_{it}, U_{it}, N_{it}, P_{it}. We define an individual as not working in a calendar year ($N_{it} = 1$) if $HOURS_{it} = 0$. She is defined as unemployed in a calendar year ($U_{it} = 1$) if she had positive hours in the year ($N_{it} = 0$) but reported some weeks of unemployment during the year. Finally, she is defined as employed ($E_{it} = 1$) if she worked during the year and had no unemployment. At times, we use participation as a variable in the model, which we define as $P_{it} = 1 - N_{it} = E_{it} + U_{it}$.

Nonlabor Income. NLY_{it}. This is defined at the household level. That is, it is not calculated individually for the husband or the wife. It is drawn from PSID questions about the household's taxable income and transfers received; from these values, we subtract earnings to arrive at nonlabor income. The PSID does not ask questions about taxable income two years ago, so nonlabor income is only available in even years after 1997. Our estimation of the nonlabor income process accounts for this.[12] We impose a floor of \$500 prior to taking logs.

Family Income Per Adult Equivalent. Y_AE_{it}. Family income Y_{it} is the head plus wife's taxable income plus transfers received. It is censored from below at \$2,000. AE_{it}, the number of adult equivalents, equals

$$1 + .7MAR_{it} + .5 \times (\text{Number of children between 0 and 18 years of age})$$

Y_{it} and $Y\_AE_{it} = Y_{it}/AE_{it}$ are used to evaluate model fit but not in the estimation of the model.

Marriage and Marital Duration. MAR_{it} and $MDUR_{it}$. We define a sample member as married if they are legally married or had been cohabiting with someone for more than one year. We use various imputation procedures, the PSID's Marital History File, and move-in, move-out data to fill

[11]For example, if a PSID respondent reports 1500 for annual earnings in 2012 (the base year of our price index) and 300 for hours, then we set the wage to the floor of \$6.50 rather than to \$5.00 (5.00=1500/300) but do not adjust earnings. In this case, the log of our earnings measure—log(1500)—is less than sum of the logs of the hours and the wage measure: log(300) + log(6.5).

[12]As we explain below, we assume nonlabor income has an AR(1) component and only estimate the parameters of this AR(1) process using the data before 1997.

in marital status and duration information for even years (i.e. non-survey years) after 1997.

Children. CH_{it}. In our models we typically represent kids using variables counting the number of children between the ages 0–5, 6–12, and 13–18. We draw information about children from the Childbirth and Adoption file of the PSID.

Education. $EDUC_i$. When the PSID has multiple reports for a person's education, we use the average of the reports.

Potential Experience. PE_{it}**.** We define this as age minus 6 and minus the highest of either 9 or the sample member's education.

Birth Cohort. B_i**.** The individual's year of birth.

3 A Model of Earnings, Marriage, and Family Income Across Cohorts

We employ essentially the same econometric model as AGHV, which provides a more detailed discussion. As a result, in describing our model here, we often borrow descriptions verbatim from AGHV. Our goal is to provide a self-contained explanation of the model, allowing the reader to comprehend the approach with minimal reference to AGHV.

To study the sources of variation in y_ae_{it}, we need to model earnings, the presence of a spouse (and their earnings), nonlabor income, and the presence and ages of children. To this end, we specify and estimate equations for wages, hours, employment status, nonlabor income, marital status, and fertility, as well as a new spouse's age, employment status, education, and wages.

Our choice of what variables to include in each equation is guided by the large literature on wage rates, labor supply, hours constraints, marital sorting, marriage, and fertility— as well as by the need to allow for change across cohorts. Our specifications are only loosely informed by structural lifecycle models of wages, labor supply, marital choices, and fertility, which are typically forward looking. For example, our hours model excludes wealth and expectations about future wage rates or the likelihood of a divorce. Adding expectations to the model would require additional equations for them and greatly complicate identification. Because expectations of future variables are excluded, the effect of shocks in our model include effects of new information about future variables. Current or lagged values of explanatory variables on, for example, labor supply, include direct effects as well as indirect effects operating through expectations. The same comment can be made about much of the "reduced form" literature on the outcomes in our model.

The parameters of our model are influenced by tax and transfer policies, marriage law, social norms, discrimination law, and other environmental factors. The time and birth cohort variables will pick up changes in these factors.

In choosing functional form and what variables to include, particularly interactions with birth year, we had to consider the risk of over fitting. We selected variables, the order of the polynomials, and the interactions in each of the equations using a combination of AIC, joint significance, and individual statistical significance, as well as guidance from the literature. In a number of cases, we left in variables even though they were not individually significant either because previous research suggested inclusion or for symmetry in the model across genders.

Most of the equations are estimated individually, with the estimation method varying from equation to equation. We chose to take this equation-by-equation approach, rather than estimating the equations jointly, because of the complexity of estimating such a large system using the simulation-based estimation methods that would be required. An alternative strategy would be to work with a more parsimonious formulation that is more closely tied to a structural model. We leave that difficult task to future research. We highlight some of the problems with our estimation strategy as we go through the model and list some additional ones at the end.

The model is far too large to fully detail in the body of the paper—there are 42 equations and 876 parameters. While Appendix B, taken from AGHV, provides more details regarding the model and reports all of the model estimates, the remainder of this section provides a high-level overview of each of the model's components. We present the model in six parts. The first part deals with the initial conditions at age 25 (for employment, marital status, and number of children) conditional on the exogenous variables in the model: education, gender, and cohort. The second part handles earnings and the components therein: hours, wages, and employment status. The third is for nonlabor income, which depends on gender and current and lagged marital status. The fourth part concerns marital transitions, while the fifth part concerns marital sorting. The sixth deals with fertility.

3.1 Initial Conditions at Age 25

The model starts at age 25. Education, gender, and birth cohort are exogenous. For each education, gender, and birth cohort grouping, we estimate the joint distribution of labor market status (N, E, and U), marital status, marital duration, and number of children using data on sample members between the ages of 23 and 27.[13] The birth cohort combinations are 1935–1944, 1945–1953,

[13]For the initial conditions, we divided years of education into two categories, less than or equal to 12 years and more than 12 years.

1954–1962, and 1963–1974.[14] To determine the initial age distribution of children, we estimate the joint probability of the possible combinations of ages conditional on the number of children, pooling across all cohorts. Because unemployment data is missing for many women before 1974, and because many individuals in the first cohort grouping are not observed around 25 (they were too old by the time the PSID began), we adopt various procedures to impute these initial conditions for sample members before estimating the joint distributions. See Appendix B.1.

3.2 Earnings

The earnings model is composed of (1) equations governing hourly wage rates, (2) equations for annual employment status, and (3) an equation for annual work hours conditional on participation.

3.2.1 Log Hourly Wages

The observed wage rate $wage_{it}^{*}$ equals the log hourly wage $wage_{it}$ plus classical measurement error where $wage_{it}$ is given by:

$$\begin{aligned}
wage_{it} &= P_{it} \cdot wage_{it}^{lat} && (1)\\
wage_{it}^{lat} &= X_{it}^{w}\gamma_{X}^{w} + \mu_i + \omega_{it} + \varepsilon_{it}^{w} && (2)\\
\omega_{it} &= \gamma_0^{\omega} + \rho^{\omega}\omega_{i,t-1} + \gamma_U^{\omega}U_{i,t-1} + u_{it}^{\omega} \text{ if } age_{it} > 25 && (3)\\
\omega_{it} &= \omega_{i25} \text{ if } age_{it} = 25\\
\mu_i &= N\left(0, \sigma_{\mu}^2\right); \; u_{it}^{\omega} \sim N\left(0, \sigma_{u^{\omega}}^2\right); \; \varepsilon_{it}^{w} \sim N\left(0, \sigma_{\varepsilon^{w}}^2\right).
\end{aligned}$$

While all sample members have a latent wage given by (2), equation (1) says that we only observe this for an individuals who worked positive hours ($P_{it} = 1$). This formulation captures the idea that worker skills and worker-specific demand factors evolve during a nonemployment spell.

The latent wage $wage_{it}^{lat}$ depends on a set of regressors X_{it}^{w}, a permanent wage component μ_i, an autoregressive wage component ω_{it}, and the i.i.d. shock ε_{it}^{w}. The vector X_{it}^{w} contains marital status MAR_{it}; a cubic time trend; education $EDUC_i$; potential experience PE_{it}, PE_{it}^2, and PE_{it}^3; and the interaction between $EDUC_i$ and both PE_{it} and PE_{it}^2. For women only, it also contains the square of birth cohort B_i, the vector CH_{it} containing counts of children aged 0-5, 6-12, and 13-18; interactions between CH_{it} and B_i and B_i^2; and interactions between MAR and B_i and

[14] Note that these cohort groupings are for the drawing of initial conditions. They are more granular than the cohort groupings of early, baby boom, and late that we use in the analysis.

B_i^2. Also for women only, X_{it}^w includes the labor force status vector $LFS_{i,t-1}$, which consists of $P_{i,t-1}, P_{i,t-2}, P_{i,t-3}, U_{i,t-1}$, and $U_{i,t-2}$. Because $LFS_{i,t-1}$ and the marital status variables may be correlated with μ_i, we instrument them using deviations from their i-specific means.[15]

The unobserved stochastic wage component ω_{it} depends on $\omega_{i,t-1}$, the lag of unemployment $U_{i,t-1}$ (for men), and the mean-zero wage shock u_{it}^{ω}. We estimate the variances of the unobserved components of wages by estimating (2) with 2SLS, using the residual from this regression to estimate (3) with 2SLS, and then using the method of moments. We also estimate the variance of an i.i.d. measurement error term. See Appendix B.2 for more details and Appendix Tables B.1a and B1.b for all parameter estimates.

The value of $\hat{\rho}^{\omega}$ is 0.810 (.027) for men and 0.770 (0.044) for women, which suggests less persistence than some other studies have found. The standard deviation of the AR(1) innovations, $\hat{\sigma}_{u^{\omega}}$, is 0.183 (0.007) for men and 0.186 (0.010) for women. Permanent heterogeneity is large. The estimate of σ_{μ} is 0.350 (0.011) for men and 0.331 (0.013) for women. It is a key contributor to the variance of earnings and family income.

3.2.2 Annual Labor Market Status (E_{it}, U_{it}, N_{it})

We model E_{it}, U_{it}, N_{it} using a dynamic multinomial logit model with normally distributed random effects, treating N_{it} (nonparticipation) as the reference category. Let the latent variables V_{it}^E and V_{it}^U denote the value of employment and of unemployment in the current period relative to the value of nonparticipation. The equations for V_{it}^E and V_{it}^U are

$$V_{it}^E = X_{it}^E \gamma_X^E + \nu_i + \xi_t^E - \xi_{it}^N \quad (4)$$
$$V_{it}^U = X_{it}^U \gamma_X^U + \nu_i + \xi_t^U - \xi_{it}^N \quad (5)$$

The vectors X_{it}^E and X_{it}^U contain a cubic time trend, $EDUC_i$, and a cubic in PE_{it}. They also include MAR_{it}, the vector CH_{it} containing counts of children aged 0-5, 6-12, and 13-18, B_i^2, B_i^3 and $CH_{it} \cdot B_i$. X_{it}^E and X_{it}^U also contain interactions of $EDUC_i$ with a cubic in birth cohort. Importantly, they also include $E_{i,t-1}$ and $U_{i,t-1}$. For women, most variables are also interacted with MAR_{it}, including the time trend and birth cohort.[16] Finally, the model contains a normally

[15]To simulate wages for female sample members, we must simulate the lags of participation and unemployment for women at age 25. We do so using separate probit regression for $P_{i,t-1}$, $P_{i,t-2}$, $P_{i,t-3}$, $U_{i,t-1}$, and $U_{i,t-2}$ estimated using women between ages 23 and 27.

[16]We excluded interactions between the child counts and birth cohort because they are not significant for women, but model simulations show that the effect of children on employment has declined substantially across cohorts (not reported).

distributed random effect ν_i. The random effect has a coefficient of 1 in the latent indices for E and U relative to N. We refer to ν_i as the permanent employment component.

In most cases we do not observe initial conditions. As discussed in AGHV, this is likely to lead to an overstatement of state dependence and an understatement of σ_ν^2. We do not address this but suspect it leads to an understatement of the contribution of ν_i to the variance of earnings. As we discuss below, that contribution is large for the later cohort as is. The multinomial logit coefficients are presented in Appendix Table B.2.

3.2.3 Log Annual Hours

The equation for log hours conditional on working positive hours is

$$hours_{it}^* = X_{it}^h \gamma_X^h + e_{it}^h \ \text{ if } P_{it} = 1$$

For both men and women, we pool singles and married but include MAR_{it} in X_{it}^h. We included B_i^2 and cubics in PE_{it} and t. The equations also include the wage and U_{it}, which picks up effects of hours lost to unemployment. For women, we include CH_{it} and allow the effects of most variables to depend on marital status. We also include the spouse variables $wage_{ist}$ and U_{ist}. (Throughout, we use the letter s in subscripts to indicate a spouse's variable.) Some of the variables are interacted with B_i, t, or powers of each. Estimates are reported in Appendix Table B.3a.

The $hours_{it}^*$ error term is

$$e_{it}^h = \eta_i + \omega_{it}^h + \varepsilon_{it}^h + me_{it}^h$$

where

$$\omega_{it}^h = \rho_{\omega^h}^h \omega_{i,t-1}^h + u_{it}^h.$$

The variable η_i is an unobserved permanent hours component, ω_{it}^h is the autoregressive component with innovation u_{it}^h, ε_{it}^h is the i.i.d. error, and me_{it}^h is measurement error. All errors have normal distributions. As described in the table notes, we estimate by 2SLS with the wage variables, marital status, and CH_{it} treated as endogenous. We estimate σ_η, $\rho_{\omega^h}^h$, σ_{u^h}, and σ_{ε^h} by the method of moments. See Appendix B.3 and Appendix Table B.3b.

The estimates of σ_η are 0.148 (0.007) for men and 0.223 (0.018) for women, indicating substantial permanent heterogeneity in hours conditional on employment status. However, they play only a minor role in the variance decompositions of earnings and family income. The hours shocks are large and persistent enough to be an important factor in the variance decompositions.[17]

3.2.4 Log Annual Earnings

In the simulation model log earnings are defined as:

$$earn_{it} = wage_{it} + hours_{it} \text{ if } P_{it} = 1 \tag{6}$$
$$= ln(1300) \text{ if } P_{it} = 0 \tag{7}$$

where $wage_{it}$ and $hours_{it}$ are the simulated wage and simulated hours (without measurement error). When we simulate, we impose floors of $ln(6.5)$ and $ln(200)$ on $wage_{it}$ and $hours_{it}$, respectively. We also set $hours_{it}$ to $ln(200)$ when $P_{it} = 0$. Consequently, the minimum of simulated $earn_{it}$ is $\ln(200) + \ln(6.5) = ln(1300)$.

3.3 Nonlabor Income and Family Income Per Adult Equivalent

Nonlabor income depends on marital status and gender. Specifically, for every marital transition m (single-to-single, single-to-married, married-to-single, and married-to-married) and each gender g, we estimate the following model for those over the age 25:[18]

$$\begin{aligned} nly_{it} =& X_{it}^{nlgm}\gamma_X^{nlgm} + \omega_{it}^{nl} \\ \omega_{it}^{nl} =& \rho_{gm}^{nl}\omega_{i,t-1}^{nl} + \varepsilon_{it}^{nlgm}. \end{aligned}$$

We also estimate $nly_{it} = X_{it}^{nlgm}\gamma_X^{nlgm} + \omega_{it}^{nl}$ for single men at 25, single women at 25, and married individuals at age 25. We use these equations to simulate initial values at age 25 of nly_{it} and ω_{it}^{nl}. Hence we estimate a total of 10 sets of equations (one for each gender-age-marital-combination group). All errors are normally distributed with gm-specific variances.[19] The estimates are in Appendix Tables B.4a and B.4b.

[17] The values of ρ^h are 0.666 (0.039) for men and 0.722 (0.039) for women. The standard deviations of the shocks u_{it}^h to ω_{it}^h are 0.195 (0.017) for men and 0.244 (0.019) for women. The standard deviations of the initial conditions for ω_{it} at age 25 are 0.298 (0.017) for men and 0.386 (0.018) for women. The standard deviations of the shocks u_{it}^h to ω_{it}^h are 0.195 (0.017) for men and 0.244 (0.019) for women. The standard deviations of the i.i.d. shocks ε_{it}^h are 0.232 (0.011) for men and 0.349 (0.013) for women.

[18] For married-to-married transitions, we did not estimate separate models for men and women, as nonlabor income is observed at the household level.

[19] We estimate the first equation using OLS for a given gender-marital-transition combination. We then use the residuals from this first regression to estimate the ρ_{gm}^{nl} using OLS, along with the variance of ε_{it}^{nlgm}. Because nonlabor income data are not available in odd years after 1996, we only use data through 1996 to estimate the ρ_{gm}^{nl}.

3.3.1 Family Income Per Adult Equivalent

In the simulation model and in the data, the level of family income is the sum of earnings of the individual and the spouse (if present) plus nonlabor income:

$$Y_{it} = exp^{earn_{it}} + exp^{earn_{sit}} + exp^{nly_{it}},$$

where $earn_{sit}$ is log earnings of the spouse. Family income per adult equivalent is $Y\_AE_{it} = Y_{it}/AE_{it}$, where AE_{it} is the OECD's adult equivalence measure, which accounts for returns to scale in home production and the lower resource use of children. The measure is

$$AE_{it} = (1 + 0.7MAR_{it}) + 0.5\,(\#\,of\ children)\,.$$

Our focus is on the log, y_ae_{it}.

3.4 Marriage

3.4.1 Single to Married

As we noted earlier, "married" refers to both legal marriages and cohabitation for more than 1 year. After age 25 transitions into marriage are determined by the probit model

$$MAR_{it} = I[X_{it}^{SM}\gamma^{SM} + u_{it} > 0] \text{ if } MAR_{i,t-1} = 0,$$

which we estimate on the pooled sample of men and women. Here X_{it}^{SM} includes a constant and the female indicator FEM_i. It also includes education, $wage_{i,t-1}$, $P_{i,t-1}$ and $U_{i,t-1}$, a quadratic in age, and the interaction of all of these variables with FEM_i. In addition, we include the index $CH\_VAR1_{i,t-1}$ measuring the presence of young children, a cubic time trend, $FEM_i \cdot B_i$, $FEM_i \cdot B_i \cdot EDUC_i$, B_i^2, and interactions of $CH\_VAR1_{i,t-1}$ with B_i and B_i^2. The probit coefficients are displayed in Appendix Table B.5. Space constraints preclude a discussion.

3.4.2 Married to Married

The marriage continuation probability is determined by the probit model

$$MAR_{it} = I[X_{it}^{MM}\gamma^{MM} + \&_{j(i,t)} + \varepsilon_{it}^{MM} > 0] \text{ if } MAR_{i,t-1} = 1,$$

estimated on the pooled sample of married male and female sample members. The vector X_{it}^{MM} includes a constant, FEM_i, $CH\_VAR1_{i,t-1}$, the absolute differences between the education levels, ages, and wage rates of the spouses, and a cubic in t.[20] It also includes an age cubic, education, $wage_{i,t-1}$, $P_{i,t-2}$, and $U_{i,t-2}$ for each spouse, all with gender-specific coefficients.[21] The cohort variables include B_i^2, and interactions between B_i and several of the variables.[22] We include the square root, level, and square of marriage duration and the interactions of these terms with B_i and with a quadratic in t. The model also includes the normally distributed marriage-specific heterogeneity term $\&_{j(i,t)}$, where j indexes the marriage that i is in at year t. We ignore the fact that some of the marriage spells in the sample are left-censored, which creates an initial conditions problem in the presence of duration dependence.[23] The probit estimates are in Appendix Table B.6.

3.5 Spouse Characteristics at the Start of a Marriage

To be able to simulate lives, we need to model all spouse characteristics that influence the path of own and spouse earnings, unearned income, and/or the divorce probability. Here we briefly discuss the models of spouse's education and wages, which are key. Appendix Tables B.7–B.11 display the estimated model coefficients.

3.5.1 Spouse's Education

For marriages in progress at age 25, spouse education $EDUC_{si}$ depends on $EDUC_i$, age, t, t^2, $CH05_{it}$, and the interaction between education and a quadratic in t. For marriages that start after the sample member is 25, we use $CH05_{i,t-1}$, $CH612_{i,t-1}$, and $CH1318_{i,t-1}$ instead of $CH05_{it}$, add B_i^2, and replace the interaction terms involving t with B_i. All equations are gender-specific.

[20] The absolute differences are around the mean of the corresponding arithmetic differences in the sample.

[21] We use second lags because in the event of a divorce, $P_{i,t-1}$ and $U_{i,t-1}$ are missing for the nonsample member spouse after the switch to biennial interviewing in 1997.

[22] The model includes the interaction of B_i with the absolute difference in education levels and gender-specific interactions of B_i with education and $P_{i,t-2}$.

[23] To improve our fit of the age profile of marriage-to-marriage transition probabilities for the later cohort, we employed an additional correction to the model when simulating. To produce the correction, we first simulated 500 lives for each member of our PSID sample using only the estimated marriage equation from Appendix Table B.6 (and the rest of the model). Then, we estimated a probit regression model of marriage-to-marriage transitions on a pooled data set of both the simulated data and the PSID data. The right-hand side of the probit model includes a cubic in age, a cubic in cohort, a quadratic in year and an interaction of these terms with a dummy indicating whether the observation is from the PSID (instead of a simulated observation). The estimated coefficients on the interactions with the PSID variables (and the PSID intercept) are used to form a regression index that we added to our model of marriage-to-marriage transition probabilities when simulating the model.

We estimate by OLS. The mean squared error of the equations provides age- and gender-specific estimates of the variance of $\varepsilon_{it}^{ED_s}$, the random component of spouse's education. We assume $\varepsilon_{it}^{ED_s} \sim N(0, \sigma_{ED_s}^2)$. The estimates are reported in Appendix table B.7.

3.5.2 Spouse's Age

We estimate gender-specific regression models of a new spouse's age. We do this separately for marriages in progress at age 25 and marriages that start after age 25. Spouse's age is allowed to depend on education, age polynomials, year polynomials, cohort polynomials, $CH05_{i,t-1}$, $CH612_{i,t-1}$, and $CH1318_{i,t-1}$ and the interaction between B_i^2 and age. We assume errors are normally distributed. Appendix Table B.8 presents the estimates.

3.5.3 Spouse's Labor Market Status

To determine a spouse's initial employment status (N, E, or U), we estimate multinomial probit models of employment status separately by gender and by whether it is an ongoing marriage at age 25 or one that begins afterwards. Spouse's employment status depends on $EDUC_i$, the wage, PE_{it}, PE_{it}^2 and PE_{it}^3 (females only), $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, employment status, and a quadratic in calendar time. We report the estimates for the models for spouses after age 25 in Tables B.9 and B.10. We assume that spouses do not sort directly on the employment heterogeneity term ν_i or on the hours heterogeneity term η_i.

3.5.4 Spouse's Permanent Wage Component (μ_{si}) and Transitory Component (ω_{sit})

Recall that the subscript s indicates that a variable or parameter refers to the spouse. The subscripts f or m indicate the gender of the individual or the spouse.

The model for μ_{sfi} of the female spouse is

$$\begin{aligned}
\mu_{sfi} &= \gamma_m^{\mu_s}\mu_{mi} + \tilde{\mu}_{sfi} \\
Var\left(\mu_{sfi}\right) &= Var\left(\mu_{fi}\right) \\
&\quad \tilde{\mu}_{sfi} \sim N\left(0, Var(\mu_{sfi}) - (\gamma_m^{\mu_s})^2 Var(\mu_{mi})\right).
\end{aligned}$$

The value of ω_{sfit_0} for a marriage that starts in t_0 is related to ω_{mit} according to

$$\begin{aligned}\omega_{sfit_0} &= \gamma_m^{\omega_s}\omega_{mi,t_0-1} + \tilde{\omega}_{sfit_0} \\ Var(\tilde{\omega}_{sfit_0}) &= Var(\omega_{sfit_0}) - (\gamma_m^{\omega_s})^2 Var(\omega_{mi,t_0-1}) \\ & \tilde{\omega}_{sfit_0} \sim N\left(0, Var(\tilde{\omega}_{sfit_0})\right).\end{aligned}$$

Because $\gamma_m^{\omega_s}$ is not well identified, we restrict it to equal the coefficient $\gamma_m^{\mu_s}$ linking the spouse's permanent wage component μ_{sfi} to μ_{mi}. We also restrict variances for female (male) spouses to be the same as the variances for female (male) sample members. After a marriage starts, ω_{sfit} evolves according to the wage model (3) for women. When we simulate the model, we draw μ_{sfi} from $N(\gamma_{m\mu}^{\mu_s}\mu_i, Var(\tilde{\mu}_{sfi}))$. We draw ω_{sfit} from $N(\gamma_{m\omega}^{\omega_s}\omega_{mi,t_0-1}, Var(\tilde{\omega}_{sfit_0}))$. We model the wage of male spouses using the same approach as for female spouses.

We use the method of moments to fit γ^{μ_s} and $\gamma_m^{\omega_s}$ to the covariances of the wage residuals of the sample member and the spouse at various leads and lags during the marriage, subject to the restriction $\gamma_m^{\omega_s} = \gamma_m^{\mu_s}$. See Appendix B.4. All parameters depend on whether the sample member was born before 1962.[24] The estimates are shown in Appendix Table B.11. As we discuss below, sorting is large enough that it substantially increases the contribution of μ_i to inequality in family income, especially for women.

3.6 Fertility after Age 25

Births of children after age 25 are determined by gender- and marital status-specific probit models of the form

$$BIRTH_{it} = I[X_{it}^B\gamma^B + u_{it}^B > 0].$$

For unmarried individuals, the explanatory variables are $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, a cubic in age, a quadratic in year, B_i^2, $EDUC_i$, and the interaction between $EDUC_i$ and a quadratic in B_i. For married individuals we add a quadratic in spouse's age and also year cubed. We restrict the sample to ages below 51. The probit estimates are shown in Appendix Table B.12. A shortcoming of the model is that fertility is not determined jointly with labor supply and wage rates.

[24] This split at 1962 corresponds with the end of our baby boom cohort.

3.7 Some Limitations of the Model and Estimation Strategy

Here we briefly highlight some limitations of the model and of our estimation strategy, some of which were already mentioned. First, we treat education as exogenous in the model. Consequently, it may pick up part of the effects of unobserved heterogeneity in the equations for the wage rate, labor market status, work hours, and the marriage probability. This affects the interpretation of the contribution of education to the income and earnings variances. Second, we account for endogeneity of marriage and labor market status in the hours equation and wage equations due to permanent heterogeneity, but in the model simulations we assume that μ_i, ν_i and η_i are mutually uncorrelated. Third, we assume all of the i.i.d. error components in the model equations, as well as the innovations in ω_{it}^h and ω_{it}, are mutually uncorrelated. For example, we do not allow for an error influencing fertility that might be related to the employment and hours shocks separately from the direct influence of children on employment and hours. Nor do we allow for unobserved health shocks that directly affect both marriage transitions and work hours. Fourth, the model has rich dynamics, as the impulse response functions reported in AGHV demonstrate, but they are also necessarily restricted. Finally, we have already pointed out that we do not address initial conditions bias when estimating the dynamic multinomial model of labor status in the presence of heterogeneity, or when estimating the model of marriage continuation.

3.8 Model Fit

To evaluate fit, we use our estimated model to simulate 500 lives for each member of our PSID estimation sample and compare the simulated data against the actual data along several dimensions. We specifically evaluate fit for each of our three cohort groupings: early, baby boom, and late.[25] In the simulations, the birth cohort, gender, and education of each simulated individual match the values of a corresponding PSID sample member. We only include simulated values that correspond to the specific ages when the PSID sample member was observed and contributed to our sample.

Overall, our model fits the data reasonably well, though the fit is far from perfect. This is to be expected, considering that—due to its size and complexity—the model is estimated equation by equation, rather than by matching data simulated from the full model to the PSID. The model's misses tend to be more pronounced at younger ages for individuals in the 1935-44 cohort. One reason is that the PSID has relatively few observations for this cohort early in the life cycle. Due to space constraints, we relegate the discussion of fit to Appendix C and the associated results in

[25] As a reminder, the birth years corresponding to these groups are 1935–1944, 1945–1962, and 1964–1974.

Appendix Tables C.1-C.3 and Appendix Figures C.1-C.10.

4 Using Simulated Data to Summarize the Effects of Personal Characteristics and Spouse Characteristics on Earnings and Income

Because of the size of the model, the linkages among the equations, and the dynamics, the most efficient way to provide insights into how key variables affect earnings and income is to use simulated data to measure the overall effect of observed and unobserved personal characteristics and spouse characteristics on income and earnings. To this end, we first use the model to simulate 100 lives for each sample member in our PSID sample. We then regress the variables y_ae_{it} and $earn_{it}$ on $EDUC_i$, the permanent wage component (μ_i), the hours permanent component (η_i), and the permanent employment component (ν_i) by birth cohort and gender, when age is between 26 and 50 inclusive. We also include the wage and hours autoregressive components ω_{it} and ω_{it}^h in the regressions. Prior to estimation, we renorm the explanatory variables to have a standard deviation of 1 for each group. Consequently, the squares of the coefficients give a rough sense of how much the variable contributes to the variance of the outcome in the case of all of the variables except for ν_i.[26] We report separate estimates for all person-year observations and for observations on married individuals. For married individuals, we estimate a separate set of regressions to which we add $EDUC_{si}$, μ_{si}, η_{si}, and ν_{si}. Comparing the coefficients with and without the spouse variables provides an easy way to assess the extent to which the effect of personal characteristics on outcomes operates directly versus through the spouse.

The results for family income and earnings are in Table 1. The row labels indicate the explanatory variable and whether the estimates refer to family income or earnings (the latter in italics). The results for $wage_{it}$ and $hours_{it}$ are in Appendix Table D.1.

We also estimate separate regressions for the age ranges 26 to 30 and 46 to 50. These results are helpful in understanding changes with age in the contribution of particular variables to the variance of earnings and income. They are reported in Appendix tables D.2 and D.3.

Returning to Table 1, the coefficients for the effect of education on y_ae_{it} are in the first row. For the early cohort, the effect is 0.291 for all men (column 1a) and 0.298 for all women (4a).

[26] In the case of ν_i, the contribution is understated because of strong nonlinearity in the effect of ν_i on E_{it} and U_{it}, and the fact that employment status interacts with hours worked and the wage rate in determining earnings. When $P_{it} = 0$, $earn_{it}$ is set to its lower bound.

These values reflect a strong link between education and earnings for both men and women. The corresponding regressions for *hours* and *wage* indicate that a substantial portion of the effect is through *hours* (Appendix Table D.1). When we restrict the sample to married individuals, the effect of education for women is 0.287 when we exclude the spouse variables but only 0.095 when we include them. By the same token, the coefficient on $EDUC_s$ is 0.242. These results indicate that for married women in the early cohort, much of the effect of $EDUC$ on y_ae is through sorting. In contrast, for married men the effect of education declines by only 0.067 when $EDUC_s$ is controlled for, and the coefficient on $EDUC_s$ is only 0.097.

For the later cohort, the coefficient on $EDUC$ falls slightly for both men and women.[27] The regressions on the married subsamples with and without spouse variables indicate that the gap between women and men in the importance of sorting in the effect of education on family income declined substantially across cohorts. The coefficient on $educ_s$ increases for men and declines for women relative to the early cohort, reducing the female - male gap from 0.145 to only 0.042.

A one-standard-deviation increase in μ raises family income by about 0.264 for men in the early cohort but only 0.171 for women. Part of the gender difference reflects the fact that the earnings coefficient on μ is larger for men than for women, which in turn reflects differences in work hours. The gender difference in the coefficient on μ is small for single men and women (not reported), so the gender difference is primarily related to marriage.

The family income regressions on the married sample with and without spouse controls indicate that the marital return to μ is much more important for women, echoing the results for $EDUC_i$. For women, the coefficient on μ declines from 0.147 to just 0.063 when μ_s is controlled for, and the coefficient on μ_s is 0.238. For men the coefficient on μ declines by only 0.02, and the coefficient on μ_s is only 0.065. The regression results for the later cohort show that the effect of μ on $y_{-}ae_{it}$ rose for women relative to men. They also show that the female - male difference in the importance of sorting declined substantially. This will be borne out in the variance decompositions.

The effect of a one-standard-deviation increase in η on $y_{-}ae_{it}$ is much smaller than the values for $EDUC$ and μ for both men and women. It is twice as large for men in the early cohort, but the gender gap disappears in the later cohort as labor force participation of women rises. There is no sorting on η in the model, and this is reflected in the stability of the coefficient on η when adding the spouse variables to the regression. But for women η_s has a coefficient of 0.097 on $y_{-}ae$ in the early cohort compared to only 0.033 for men. The gender difference is much smaller in the later cohort, reflecting partial convergence in the labor market behavior of men and women.

[27] The decrease for men is in spite of an increase in the effect on earnings. The increase in the earnings coefficient is entirely due to *hours*.

The employment heterogeneity term, ν, has only a small effect on y_ae_{it} in the early cohort, reflecting a relatively small effect on earnings. It is much more important in the later cohort for both family income and for earnings. For men, these results are driven by an increase in the effect of ν_i on $hours$ from 0.061 to 0.191 even though σ_ν is constant across cohorts. As the employment rate of men has declined across cohorts, employment becomes more sensitive to the permanent component ν. The separate estimates for individuals aged 26-30 and 46-50 show a strong increase with age in the effects on earnings that is reflected in the effects on family income.

For women, the change in sensitivity of hours and earnings across cohorts is much smaller, but the influence of ν_i on family income increases substantially across cohorts. This reflects the growth in the share of family income contributed by married women. Among married couples, gender differences in the importance of ν_s for family income mirror gender differences in the importance of the contribution of ν.

Finally, we turn to ω and ω^h, the autoregressive transitory components of the wage and hours. First, they have similar effects on earnings for men and women. Not surprisingly, the effect of ω operates primarily through $wage_{it}$ and the effect of ω^h operates through $hours_{it}$. Second, the effects for married males on family income are more than 3 times as large as the effect for married women, but the gender disparity declines substantially across cohorts, in keeping with the pattern for the other variables. Third, the models with and without the spouse variables show only a small reduction in the family income coefficients on ω even though the link between ω_s and ω at the start of a marriage is substantial. The reason is that the link decays with marriage duration at a rate equal to the product of the estimates of ρ for men and ρ for women, which is $0.62 = 0.81 * 0.77$. (There is no sorting on ω^h in the model.) Fourth, the contributions of ω_s and ω_s^h are much larger for women than for men, but the disparity declines across cohorts.

Four common themes emerge in the results. First, one-standard-deviation shifts in the permanent and transitory components have bigger effects on family income for males than for females. Second, the opposite is true for spousal components. Third, sorting is a much larger component of the income effects of education and the permanent wage for females than for males. Fourth, gender differences have declined substantially between the early and late cohort. As we shall see, the regression analysis of the simulated data is a good guide to the variance decompositions.

5 Variance Decompositions of Family Income by Age, Cohort, and Gender

We employ the model to analyze how different sources of variation contribute to variation in family income per adult equivalent at various ages. We decompose, separately for each gender-cohort-age group, the variance (across individuals in that group) of y_ae_{it} into the contributions of multiple sources of variation. We organize our discussion of the sources of variation around five categories. The first group consists of permanent characteristics of the individual: education, the permanent wage component μ_i, the permanent employment component ν_i, and the hours component η_i. The second group consists of the individual's own "labor market shocks," by which we mean shocks an individual faces that are not related to her spouse. These are: (1) "employment shocks," the i.i.d. shocks to employment status; (2) "wage shocks," the initial draw ω_{i25} and shocks u^{ω}_{it} to the autoregressive wage component ω_{it} plus the i.i.d. wage shocks ε^{w}_{it}; and (3) "hours shocks," the initial draw ω^{h}_{i25} and the shocks u^{h}_{it} to the autoregressive hours component ω^{h}_{it} plus the i.i.d. hours shocks ε^{h}_{it}. The third category is "unearned income shocks," the initial draw and shocks to the autoregressive component of unearned income. The fourth group consists of "spouse components," which affect marriage and spouse earnings. These include (1) the random component $\varepsilon^{ED_s}_{it}$ of the spouse's education; (2) the random component $\tilde{\mu}^{s}_{i}$ of μ_{si}; (3) the spouse hours and employment heterogeneity terms η_{si} and ν_{si}; and (4) "spouse wage shocks," the random component $\tilde{\omega}_{sit_0}$ of the initial condition ω_{sit_0} and shocks u^{ω}_{sit} plus the i.i.d. wage shocks ε^{w}_{sit}. The fifth category is "marital history," the contribution of random variation in marriage histories conditional on the vector $[\mu_i, \eta_i, \nu_i, \omega_{it(a_{i25})}, EDUC_i]$.[28] In Section 5.1 we discuss the methods. In Section 5.2 we provide evidence on the variance of $earn_{it}$ and y_ae_{it} by gender and age, averaging across the three cohorts. In Section 5.3 we discuss the cohort differences in the age profiles of the variance contributions of the components. Section 5.4 presents estimates of the effects of marital sorting on inequality.

[28] Note that marriage history also influences the importance of the spouse's components. It also is driven by variation in the initial condition for marriage, the effects of marriage transition shocks, fertility shocks, and the marriage quality component $\&_{j(i,t)}$. Given space limitations, we are not considering other sources of variation, including fertility shocks and employment and hours shocks affecting the spouse.

5.1 Variance Decomposition Methods

We construct our variance decompositions as follows.[29] For each gender-cohort group, we first use our model to simulate a large number of individuals from age 25 to age 50. We use the simulated data to compute the variance (across individuals in that group) of y_ae at age 26, 30, 35, 40, 45, and 50. This is the "baseline simulation." We chose 26 as the first year because initial conditions have a large influence at age 25. We stop at 50 to reduce the degree to which we are forecasting out of sample for younger members of the recent cohort. In the subsequent simulations of the model, we systematically eliminate the variance of specific sets of random components. The difference in the variance of y_ae at a given age compared to the baseline simulation is our estimate of that component or set of components' contribution to the variance at that age. For example, to measure the contribution of the permanent wage component μ_i, we set μ_i to 0 for all individuals and simulate the model again. The difference in the variance of y_ae_{it} at each age across the counterfactual and baseline simulations is what we call $\mu_i's$ variance contribution to y_ae_{it} at each age.[30]

We use a different procedure to measure the contribution of marriage uncertainty because of the complication that marital status switches the equations governing many variables in the model. An individual's marital history between ages 25 and a_{it} is uniquely summarized by the values of $MDUR_{i25}$ and the vector of values (0s or 1s) that M_{it} takes at each age between 25 and a_{it}. For each simulated life, we construct this categorical variable $MHIST_{ia}$ for each age of interest (a_{it}=26, 30, 35, etc.). If all of the effects were linear and additive, we could first regress y_ae_{ia} on the simulated values of all variables except marriage history for a given gender, cohort, and age. We would then measure the marginal contribution to the explained variance (corrected for degrees of freedom) by adding fixed effects for each unique value of $MHIST_{ia}$. In practice, our controls consist of a 3rd-order polynomial with pairwise interactions up to the second order of variables in the vector $[\mu_i, \eta_i, \nu_i, \omega_{it(a_{i25})}, EDUC_i]$. We exclude the vector of wage, labor force status, and hours shocks, as these variables are hard to summarize in a simple way. In prior work we found that wage and employment shocks have only a moderate influence on marriage transitions.

While our focus is on $var(y\_ae_{it})$, we often discuss the results using earnings as the outcome variable in order to understand and interpret the results for y_ae. In Appendix Tables E.1–E.6 we report the variance decompositions by age, with standard errors, for log family income per adult equivalent and log earnings, as well as for log wages, log hours, log family earnings, and log family

[29]Our methodology is the same as in AGHV, except that we focus on age-specific variances rather than lifetime averages. The discussion of the methods here borrows from that paper, sometimes verbatim.

[30]We shut off variability in education by setting $EDUC_i$ to its mean by gender and birth cohort. We condition only on gender and cohort when drawing the initial values of employment, marriage, and number of children at age 25. In the case of labor force status, we draw initial values as in the baseline simulation case. After age 25, we set E_{it}, U_{it}, and N_{it} to their probabilities conditional on X^E_{it}, X^U_{it} and ν_i rather than to 1 or 0.

income.[31] Confidence intervals and standard errors are based on 500 bootstrap replications of the entire model estimation and simulation procedure.[32]

5.2 Variance Decompositions by Age

We begin by analyzing how different components of the model contribute to the variance of family income per adult equivalent at different ages. Here we abstract from differences across cohorts and average the estimates for the early, baby boom, and later cohorts to produce a single variance-age profile for each of the analyzed model components. In Section 5.3 we consider differences across birth cohorts in the variance decompositions.

Table 2 displays the average variance (across the three cohorts) of y_ae at each age for both men and women. This variance is increasing for both genders, rising from 0.46 at age 26 to 0.62 at age 50 for men. For women, the level of the variance is higher at all ages but the profile is a bit flatter, rising from 0.59 to 0.69. The cross-cohort average of the variance of $earn_{it}$ also increases with age but less so for women. (See Figure 4 panel C and D, which shows the cohort-specific profiles.)

Figure 1 presents the variance contributions of the permanent characteristics and own shocks. At each of the target ages, the figure graphs the contribution of each component to the variance of y_ae. The heading at the top of each panel identifies the variance source. As we mentioned above, the values are averages across the three cohorts.[33] The dark lines with circles refer to women, while the light grey lines with squares are for men. For example, using the figure we see that education contributes about 0.08 to $var(y\_ae_{it})$ for women at age 25 and about 0.11 at age 50.

Looking broadly at Figure 1, a few patterns stand out. First, the contributions of own characteristics to $var(y\_ae_{it})$ are larger for men than for women in most cases. This reflects the greater labor market role of married men.

Second, education, the permanent component of employment (ν), and, to a lesser extent, unearned

[31] The columns 15 and 16 of the tables E.1-E.6 also report the simulated total variance of each outcome and the percentage of the total explained by the factors we consider. The variance contributions do not sum to 100%, for three reasons. First, interactions among the factors can amplify the contribution of some factors and lead the marginal contribution of some sources to be negative. Second, we do not separately measure the contributions of all of the spouse's post-marriage labor market shocks or of the marriage match quality term $_{j(i,t)}$. Third, we do not consider the effect of random variation in the number of children, which we suspect is quantitatively significant. Columns 1-13 of Appendix Tables E.7-E.12 report the contributions to the variance of $earn_{it}$ and y_ae_{it} as a percentage of the total variance of $earn_{it}$ and y_ae_{it}.

[32] Some of the bootstrap samples lead to negative estimates for some of the model variance parameters. We discard such samples when calculating standard errors.

[33] Specifically, we take the arithmetic average of the three cohort contribution measures for each age.

income shocks (especially for women) play key roles in the rise in $var(y\_ae_{it})$ with age. The contribution of ν is only 0.018 for men and 0.007 for women at age 26 but reaches 0.12 for men and 0.087 for women at age 50. The low values at age 26 are mostly an artifact of the model, because the initial conditions at age 25 for E_{it} and U_{it} are independent of ν. But there is still a substantial age profile from age 30 on.

The contribution of education also rises with age, although it is important at all ages. This increase is particularly stark for men, for whom the variance contribution of education nearly quadruples from age 26 to age 50, from 0.038 to 0.13. (Keep in mind that because of assortative mating, part of the contributions of education, and the wage components μ_i and ω_{it} are through their spouse counterparts $educ_{si}$, μ_{si}, and ω_{sit}.)

The contribution of unearned income shocks is near 0 at early ages but rises to 0.030 for men and to almost 0.05 for women at age 50. We interpret this as reflecting the rising role of capital income over the life-cycle as well as the rising role of transfers and child support, particularly for women.

Third, most of the other components displayed in Figure 1 have somewhat flatter variance-age profiles but differ in the average level across ages. For men, the contribution of the permanent wage component (μ) decreases with age but is substantial, averaging 0.076 across age categories. For women the contribution of μ hovers around 0.05 across ages. On the other hand, for both genders the permanent hours component (η) contributes little to $var(y\_ae_{it})$.

Wage shocks and hours shocks contribute a sizable amount to the variance of y_ae for both men and women, but their combined contribution does not change much with age. The contribution of hours shocks averages is 0.057 but declines with age for men and is flat for women. The contribution of wage shocks is smaller for women than for men and increases with age, from 0.018 to 0.041 between ages 26 and 50. For men, the contribution grows from 0.036 to 0.061, peaking at age 35. The contribution of employment shocks is small for women, but increases from 0.026 to 0.057 for men.

Spouse components contribute much more to $var(y\_ae_{it})$ for women than for men, as can be seen in Figure 2, which displays the contributions of the spouse components to $var(y\_ae_{it})$. For example, the average across ages of the contribution of variation in $\tilde{\mu}_i^s$, the random part of μ_{si}, is 0.041 for women but only 0.014 for men. The contribution of $\tilde{\mu}_i^s$ for women is similar to the contribution of own μ_i (see Figure 1). Similar gaps exist for the random component of spouse wage shocks, the random component of spouse's education ($\varepsilon_{it}^{ED_s}$), and for η_{si} and ν_{si}.[34]

[34] As a reminder, spouse wage shocks refer to the random component $\tilde{\omega}_{sit_0}$ of the initial condition ω_{sit_0} and shocks u_{sit}^{ω} plus the i.i.d. wage shocks.

The contributions of $\tilde{\mu}_i^s$ and spouse wage shocks have a relatively flat age slope for both men and women. On the other hand, the contribution of $\varepsilon_{it}^{ED_s}$ and the combined contribution of η_{si} and ν_{si} increase with age. The slopes are much steeper for women than for men, reflecting the greater importance with age of their spouses' earnings. For women, the combined contribution of η_{si} and ν_{si} at age 50 is 0.041, which compares to 0.098 for own η_i and ν_i and 0.059 for own μ.

As seen in the last panel of Figure 2, the marital history component for women has the steepest variance-age slope out of all the marriage-related components, rising from 0.033 to 0.073. This is similar to the profile of the contribution of women's own permanent employment component (ν) and not much below the profile for education. In contrast, the profile for men exhibits a u-shaped pattern.

To get a better sense of the channels through which these components contribute to the age profile of $var(y\_ae_{it})$, Figure 3 presents each component's contribution to the $var(earn_{it})$. The figure shows that for both genders much of the increasing contribution of ν to the y_ae variance is through the earnings variance profile. The same is true for education for men: education has a steep variance-age profile with respect to the earnings variance, which is what drives the corresponding profile for y_ae for men.

For women, the contribution of education to $var(earn_{it})$ exhibits a U-shaped age profile, dropping dramatically from age 26 to 30, and not quite recovering by age 50. This likely reflects the fact that the effects of education on own wage rates matter less for earnings when women have young children and reduce labor supply. The transformation of the U-shaped pattern for earnings to the increasing age profile for $var(y\_ae_{it})$ suggests that for women the connection of education to the probability of being married, marriage duration, and fertility leads to an increasing influence of education on y_ae. Furthermore, the combination of educational sorting and the steep age profile of the contribution of education to the male earnings variance also increases the female age profile of the effect of education on $var(y\_ae_{it})$. In section 4, we documented the strong role that marital sorting plays for women in the effect of $EDUC_i$ on y_ae_{it}.

Notice that employment shocks are much more important for $var(earn_{it})$ than $var(y\_ae_{it})$, particularly for women, and show a large increase in importance with age. Part of the difference is due to nonlabor income, which is negatively related to work hours and to earnings. However, the difference in importance is be misleading to some degree, because it is amplified by the fact that log function is very sensitive to low values. The difference between the lower bound and typical annual earnings when work hours are positive also grows with age, as wage levels rise. Shocks into nonparticipation drive earnings to the floor of log(1300), while family income includes nonlabor income and spouse earnings. The log of family income has a lower bound of log(1300 +500) for single people and log(1300 + 1300 + 500) for married individuals. The differences in the dollar values are trivial relative to the standard deviation of earnings and family income, but the differences in the log values are large.

Finishing up with Figure 3, the other striking difference between the component contributions to the earnings variance and those for y_ae_{it} variance is the steeply negative earnings variance-age profile for marital history for women. Recall that the profile for the contribution of marital history to y_ae_{it} for women is positive and relatively steep (Figure 2). This highlights that while for women the sensitivity of labor supply to marriage declines with age, whether or not they are married has a large direct impact on their total family resources that increases with age.

5.2.1 Summary

In sum, for women we find positive and substantial variance-age profiles for the contribution of education, the permanent employment component (ν), and unearned income shocks to variation in y_ae. For men, we find a decreasing contribution of the permanent wage component (μ), and hours shocks with age. Because of the importance of spouse's earnings for overall family income for women, their spouse education and spouse η and ν also have an increasing contribution to the y_ae variance with age. For women, the contribution of marital history to $var(y\_ae_{it})$ rises with age. This reflects the importance of spouse's earnings for women and the upward sloping age profile of $var(earn_{it})$ for men.

Though the analysis of the cross-cohort averages of the variance profiles is illuminating, one would expect the decompositions to vary substantially across cohorts, for two main reasons. First, the increase in women's attachment to the labor force and the decline in marriage alters the importance of own characteristics relative to spouse characteristics. So will changes in male labor supply behavior. Second, changes in the skill premiums documented in the large literature on inequality will alter the importance of particular sources of variation in family income. It is to this generational change that we turn to next.

5.3 Cohort Differences in the Variance Decompositions

In section 5.3.1, we examine how $var(y\_ae_{it})$ and $var(earn_{it})$ have changed across the three cohorts. Then, we break down the difference across cohorts in the model components' contributions to $var(y\_ae_{it})$.

5.3.1 Cohort Differences in the Family Income and Earnings Variance

We set the stage by examining changes across cohorts in the age profiles of the simulated variances of earnings and family income. Panel A of Figure 4 graphs $var(y\_ae_{it})$ by age for women. The black circle line is for the early cohort, the grey dashed line with squares is for the baby boom cohort, and the long dashed blue line with diamonds is for the later cohort. For the early and baby boom cohorts, the variance profile is relatively flat, hovering around 0.6 at most ages. But we see a large increase in both the level and the slope between the baby boom and the later cohort. For the latter, the variance of y_ae_{it} is 0.60 at age 26, rises to 0.72 at age 45, and reaches 0.83 at age 50.

Part of the shift in $var(y\_ae_{it})$ is naturally related to earnings. Panel C graphs the age profile of $var(earn_{it})$ for women by cohort. The vertical scale is different from that of the family income graphs. Not surprisingly, the $var(earn_{it})$ for women is quite large, averaging 1.80 across ages for the early cohort. It tends to rise early in the lifecycle, level off or decline in the 30s, and then rise between age 45 and 50. The age profile is much steeper for the later cohort, rising from 1.4 at age 26 to 2.2 at age 50. The cohort average (over age) of $var(earn_{it})$ decreases by a modest amount between the early cohort and the baby boom cohort. It increases from 1.74 to about 1.89 between the baby boom and the later cohort.

Men have also experienced a large increase for the later cohort in the level and slope of $var(y\_ae_{it})$ (Panel B). The age profile of the variance is almost flat for the early cohort and averages 0.50. The average is similar for the baby boom cohort, but the age profile is steeper, starting at 0.44 at age 26 and rising to 0.59 at age 50. For the later cohort, there is a large increase in $var(y\_ae_{it})$ to an average of about 0.76 between the ages of 35 and 50. In summary, we find a big increase in $var(y\_ae_{it})$ for men, with most of the shift occurring for the later cohort.

As with women, some of the increase in the variance of men's family income comes from a similar increase in the variance of men's earnings. The cohort-specific age profiles of $var(earn_{it})$ are displayed in Panel D of Figure 4. Overall, the earnings variance is quite a bit lower for men compared to women, which is not surprising because men have less variability in work hours (see Appendix Tables E.1b and E.2b). The earnings variance for males also increases dramatically across cohorts. For the early cohort, the variance is around 0.46 at age 26 and reaches 1.2 at age 50. The profile is shifted up for the baby boom cohort, with an increase that rises with age. For the later cohort, $var(earn_{it})$ is even higher, exceeding 1 after age 30 and reaching 1.8 at age 50. Most of the increase is from work hours rather than wage rates (see Appendix Tables E.1b and E.5b).

Altogether, we find that the level and slope of the age profile of $var(y\_ae_{it})$ increased dramatically across cohorts, with most of the change between the baby boom and the later cohorts.

5.3.2 Cohort Shifts in the Contribution of Education and Permanent Characteristics

Having examined the overall change in family income variance across cohorts, we now take a look at a more detailed level at how the level and the shape of the age profiles of the contributions of individual components in the model have evolved across cohorts. We additionally examine the extent to which these changes have contributed to the overall changes in $var(y\_ae_{it})$.

Figure 5 displays the contribution of permanent characteristics to $var(y\_ae_{it})$ across cohorts for women and for men. The contribution of the permanent hours component (η) is small with a flat age profile for all three cohorts for both men (Panel B) and women (Panel A). This is unsurprising, given the small contribution of η to $var(y\_ae_{it})$ that we discussed in Section 5.2. The level and negative slope of the age profile of the contribution of μ to $var(y\_ae_{it})$ is also similar across cohorts for men, with an average (across age) of 0.073, 0.075, and 0.079 for the three cohorts.

In contrast, the age profile of the contribution of μ_i for women has evolved toward the profile for men. For women, the low but increasing age profile in the early cohort (averaging about 0.032 across ages) shifted to a higher and slightly decreasing profile in the late cohort (averaging about 0.066 across ages). The rise with age in the contribution of μ_i in the early cohort reflects women's increasing labor supply later in life as children grow up. Because women in later cohorts were more permanently attached to the labor force throughout their lives and work longer hours, the contribution of μ rose at all ages and the profile flattened.

The contribution of v, the permanent employment component, experienced the largest evolution across cohorts. For both men and women, the upward sloping age profile in the early cohort shifted up and steepened successively across the baby boom and later cohorts. For men, the average contribution across age categories increased from about 0.027 to 0.11 between the early and late cohorts. For women, the increase is from 0.020 to 0.075. The increased importance of ν is due to its increased importance for $var(earn_{it})$. Appendix Figure E.1 presents the age profile of the contribution of permanent characteristics to variation in earnings. For both men and women, shifts in the contribution of ν to the age profile of $var(earn_{it})$ follow the same pattern as the shifts in the contribution of ν to var(y_ae_{it}). Averaging over age, its contribution to $var(earn_{it})$ rose from about 0.175 to 0.476 across cohorts of women, with slightly lower values for men.

Why did the age profile of the contribution of ν to $var(earn_{it})$ shift up across cohorts? Using simulated data from the model, we find that the reasons differ by gender. For men, the decline in annual labor market participation plays an important role. In the simulated data the mean of labor market participation P_{it} at age 50 declined from 0.96 to 0.90. The reduction in the average participation rate raises sensitivity to ν_{it}. In the language of our employment model and taking men as an example, the very high attachment to the labor force manifests as high values of the model's regression indices for the latent values of E_{it} and U_{it} relative to nonparticipation, $X_{it}^{E}\gamma_{X}^{E}$ and $X_{it}^{U}\gamma_{X}^{U}$. As their attachment to the labor force declines with age and across cohorts (Binder and Bound, 2019), differences in ν assume a larger role in variation in P_{it} and thus in earnings, which then feeds into $var(y\_ae_{it})$. The participation status of men with lower values of ν are more sensitive to the i.i.d. shocks when the distributions of $X_{it}^{E}\gamma_{X}^{E}$ and $X_{it}^{U}\gamma_{X}^{U}$ are lower. Appendix Tables E.1b, E.3b and E.5b show that ν raises the variance of *hours* across cohorts but not *wage*. A secondary factor is that the mean of earnings conditional on participating has increased by 0.05, reflecting a drop of 0.04 in *hours* that is more than offset by an increase of 0.09 in *wage*. This makes employment status more consequential.

For women, the growing importance of ν is in spite of—rather than because of—an increase across cohorts in labor force participation. In the simulated data, the mean of P_{it} between age 26 and 50 rises from 0.66 to 0.83 between the early and late cohorts, and this change is reflected in a modest reduction of sensitivity of P_{it} to ν (not reported). The growing importance of ν is due to the fact that the means of $hours_{it}$ and $wage_{it}$ between age 26 and 50 increased by 0.27 and 0.24 respectively, leading to an increase in the mean of earnings conditional on participation of 0.51. Consequently, the heterogeneity in labor force participation induced by variation in ν has become more consequential for $var(earn_{it})$.

Finally, we return to Figure 5 to examine the change across cohorts in the contribution of education to the age profile of $var(y\_ae_{it})$. For men, this contribution increases substantially with age, rising from 0.027 to 0.162 for the later cohort. The slope is much less steep for the baby boom cohort. The same is true for women. Curiously, however, the profiles for the later cohort and the early cohort are similar. So changes in the contribution of education are part of the reason that the age profile of $var(y\_ae_{it})$ steepened between the baby boom and later cohort for both men and women. From the early cohort to the baby boom cohort, however, changes in the contribution of education pushed towards a flattening of the age profile of the variance of family income.[35]

[35]Note that the age profile patterns across cohorts of $var(y\_ae_{it})$ for both men and women are mirrored by the cross-cohort changes in education's contribution to the age profile of $var(earn_{it})$. Appendix Tables E.1b, E.3b, and E.5b show that for men the age profile of the contribution of education to the hours variance increased modestly between the baby boom and the later cohort. At age 50, the contribution is 0.056 for the baby boom and 0.093 for the later cohort. The contribution of education to the wage variance at age 50 declined by 0.01 between cohorts.

5.3.3 The Contribution of Own Wage, Hours, Employment, and Unearned Income Shocks.

We now turn to examine the changing contributions across cohorts of own shocks. These are the wage, hours, employment, and unearned income shocks. Figure 6 presents the age profile of their contribution to $var(y\_ae_{it})$ for women and men, respectively. The principal takeaways from the figure are fourfold. First, the shifts across cohorts in the contribution of these components is smaller than the contribution of permanent characteristics.

Second, the age profile of the contribution of wage shocks to $var(y\_ae_{it})$ for women has shifted up by a small amount. The average contribution across ages grew to about 0.038 for the later cohort from 0.021 for the early and 0.032 for the baby boom cohort.

Third, women's higher labor supply (especially in their 20s and 30s) in more recent cohorts has led to a substantial increase in the contribution of hours shocks to $var(y\_ae_{it})$.

Fourth, the level and age slope of the variance contribution of employment shocks increased across cohorts, especially for men. For men in the later cohort, the contribution rises from 0.030 at age 26 to 0.091 at age 50.

5.3.4 Summary

The analysis of the contribution of own characteristics across cohorts to the age profile of family income variance returns a key theme. It is that the converging labor market behavior of men and women has contributed in part to the steepening of the age profile of family income variance. In particular, as the prime-age labor force participation has fallen for men and wage levels and hours levels have increased for women across cohorts, the influence of ν_i on $var(y\_ae_{it})$ has grown and its contribution has steepened with age. To a lesser extent, a steepening of the age profile of the contribution of education to family income variance between the baby boom and later cohort also contributed to the overall steepening of family income variance. Additionally, the rise in female labor force participation across ages and rising wage and hours levels has increased the contribution of hours and wage shocks to family income variance, which contributed to the *level* increase in women's family income variance age profile.

5.3.5 Cohort Shifts in the Variance Contributions of Spousal Components

Having examined the cohort changes in the contributions of own characteristics, we turn to changes in the contribution of random variation in spouse components to the age profile of $var(y\_ae_{it})$. Figure 7 displays, for both women and men, the contributions of the random component $\varepsilon_{it}^{ED_s}$

of spouse's education, the random component $\tilde{\mu}_i^s$ of the spouse's permanent wage component μ_{si}, the spouse's permanent hours and employment components (η_{si} and ν_{si}), and spouse wage shocks.

Differences in the contribution to the age profile of family income variance across cohorts are minor. Part of the increased age slope in the contribution of ν to the variance of men's own earnings feeds through to a slightly increased slope in the contribution of ν_s and η_s to the variance of women's family income. Similarly, the contributions of variation in $\varepsilon_{it}^{ED_s}$, $\tilde{\mu}_i^s$, η_s, and ν_s, and in spouse wage shocks have increased across most ages for men. These increases mirror the increase in the contribution of women's education, μ, η and ν, and wage shocks to women's own family income variance. Gender differences have declined.

5.3.6 The Contribution of Marital History

The most interesting cross-cohort differences in the marriage-related factors involve marital history. On one level, the story is simple enough. For both men and women, the left panels of Figure 8 show that the slope of the age profile of the contribution of marital history variation to $var(y\_ae_{it})$ has become more positive across cohorts. In the case of men, the slope shifts from strongly negative to strongly positive. This reflects the increase in women's earnings as a share of family income across cohorts. Since women in the later cohort earn more at all ages and have a steeper age profile for $var(earn_{it})$, the age slope of the contribution of marital history to $var(y\_ae_{it})$ for men should become steeper. One might expect the decline in marriage rates overall and at older ages in particular to also increase the age slope. The reason is that as the marriage probability at a given age moves away from 1, there is more overall variation in marital history, which would naturally increase the contribution of marital history to $var(y\_ae_{it})$.

There is even more going on under the surface. To see this more clearly, the right-hand panels of the Figure 8 display marital history's contribution to the age profile of the variance of own earnings. For the most part, the cross-cohort change in the level and slope of the age profiles of the contribution to $var(y\_ae_{it})$ have been qualitatively similar to the changes for $var(earn_{it})$ for each of the various permanent and transitory components that we have considered. This is not the case with marital history.

For men, the age profile of the contribution of marital history variation to $var(earn_{it})$ has a positive slope for all cohorts, but the age profile of the contribution of marital history to $var(y\_ae_{it})$ has a negative slope for the early cohort. Because the contribution of marital history to the variance of unadjusted family income, $var(y_{it})$, has a positive slope in the early cohort (see Appendix Table E.1a), we infer that the negative age slope of the contribution to y_ae_{it} is due to the influence of marital history variation on the number of adult equivalents, including children. We speculate that because most men in the early cohort were married and had children, variation in marital history had a larger impact on variation in number of children early in life. In the case of y_ae_{it}, this declining contribution with age of variance in the number of children outweighed the positive slope of the contribution of marital history to $var(y_{it})$.

For women, what stands out from comparing the age profile of marital history's contribution to $var(earn_{it})$ versus $var(y\_ae_{it})$ is that the age profile of marital history's contribution to $var(y\_ae_{it})$ always has a positive slope, even though its contribution to women's earnings has a very negative slope in the early cohort. This negative slope for earnings has decreased (in absolute value) in later cohorts, but still remains somewhat negative. In early cohorts, young single women worked much more than married women; hence marital history had a very large impact on the variation of earnings for women at younger ages. A good indication of this is that marital history contributes 0.249 to $var(hours_{it})$ for women aged 26 to 30 in the early cohort but only 0.035 for women in the later cohort (Appendix Tables E.2b and E.6b).[36] Eventually, most women in the early cohort married and stopped working (often returning to work once children are older), so the influence of variation in marital history on women's earnings waned with age. As women have increasingly worked whether married or not at all ages, the level contribution of marital history to earnings has declined and its negative age profile dampened significantly. The decline in fertility rates in the baby boom and later cohorts contributed to this pattern.

The fact that the age profile of marital history's contribution to $var(y\_ae_{it})$ has always been positive for women reflects the outsized importance of spouse's earnings for women's family income. As variation in marital history is a stronger contributor to whether someone is married at later ages in the early cohort, the contribution of marital history to $var(y\_ae_{it})$ increases with age. Then (1) the flattening of the negative age profile contribution of marital history to women's earnings across cohorts and (2) the increasing, positive age profile of the contribution of marital history to men's own earnings across cohorts have combined to create an increased slope for the age profile of the contribution of marital history to variation in y_ae_{it}.

In sum, marital history has been more important than random variation in spouse characteristics in increasing the positive age profile of $var(y\_ae_{it})$ for both men and women. This, combined with the increasing slope of the contribution of the permanent employment component and education have helped fuel the increase in the slope of the age profile of $var(y\_ae_{it})$ across cohorts.

[36] Furthermore, in the simulated data, the marriage differential in earnings for women aged 26 to 50 is -1.21 in the early cohort but only -0.482 and -0.196 in the baby boom and late cohorts, respectively (not reported). The cross-cohort values for women aged 26 to 30 show an even more dramatic decline: -1.94, -0.894, and -0.434, respectively.

5.4 The Contribution of Marital Sorting to Inequality

As noted in the introduction, a number of studies have examined the extent to which income inequality would differ if marriage partners were matched entirely at random. We address this question as follows. For each gender-cohort group, we conduct a counterfactual simulation where EDUC_{si}, μ_{si}, and ω_{si} are independently drawn from their respective *marginal* distributions. We then calculate the contribution of sorting for each gender-cohort at various ages. This is determined by the difference in the variance of y_ae with sorting (as estimated in our baseline simulation) relative to the variance under random matching.[37]

Starting with education in the first panel, Figure 9 shows the effects of sorting on $var(y\_ae_{it})$, averaging across age levels. For women (solid lines) in the early cohort (labeled as "1" in the x-axis), sorting on education increases $var(y\_ae_{it})$ by 0.039, which is about 6% of the variance with sorting. The contribution falls to 0.019 for the later cohort. The values for men (dashed lines) for the early, baby boom, and late cohorts are 0.018, 0.015, and 0.011.

How does the effect of sorting vary with age? For women, the contribution is largest at age 50 (not shown). For men, it is largest at age 35 and smallest at 26.

The contribution of sorting on μ_i (second panel) is small. It is near zero for both men and women in the early cohort. It is only 0.009 for women and 0.002 for men in the later cohort. Sorting on ω_{si} (third panel) has very little effect on $var(y\_ae)$.

We conclude that sorting on education, the permanent wage component, and the autoregressive wage component leads to only a modest increase in the age specific variances of y_ae_{it}, and that the gender difference has narrowed over time. AGHV find that it plays a much more important role in the distribution of lifetime family income.

6 Concluding Remarks

By combining earnings, marriage, and marital sorting in one model, we can study the sources of variation in the log of family income per adult equivalent (y_ae_{it}) by age, gender, and birth cohort. We find that both the level and the age slope of $var(y\_ae_{it})$ increase dramatically across the 1935-44, 1945-62, and 1964-74 cohorts, especially between the baby boom and the later cohort. The person-specific (unobserved) permanent employment component had a big hand in this. For men, its average (across age categories) contribution to $var(y\_ae_{it})$ increased from about 0.027 to 0.109

[37] AGHV take a similar approach but focus on lifetime averages rather than the variance at particular ages.

between the early and late cohorts. The increase reflects greater sensitivity of employment to the value of the employment heterogeneity term as employment probabilities for men declined across cohorts from high levels, placing more of them on the margin of working. For women, the increase is from 0.020 to 0.075. It reflects the fact that average wage rates and annual hours conditional on participation rose dramatically for women, making variation in employment more consequential. For women, the contribution of the permanent wage component to $var(y\_ae_{it})$ also increased across cohorts, especially before age 40, reflecting the increased labor supply of women.

The rise across cohorts in the female share of family earnings, as well as a decline in marriage, has led to a reduction in gender differences in sources of income variation. First, the male-female difference in the importance of the individual's own characteristics has fallen. Second, the importance of variation in spouse's characteristics has risen for men relative to women. Hand in hand with this result is the finding that relative to a world of random matching, marital sorting increases $var(y\_ae_{it})$ by 0.05 for women in the early cohort but very little in the later cohort.

There are a number of possible extensions to our analysis, beyond improving the model, the data, and the estimation strategies. First, one could use the model to study the determinants of the age profiles of the *volatility* of earnings and family income.[38] Second, one can modify the model to allow additional parameters, including the shock variances, to depend on education and use it to study how education influences the variance profiles. Third, one could explore the sources of gender differences by performing a Oaxaca-Blinder type analysis replacing particular equations for women with the equations for men. Fourth, one could extend the model to more complicated family structures and distinguish co-habitation from marriage.

Finally, the large differences by age, gender, and cohort in the family income and earnings variance that we find have important implications for consumption, savings, and wealth holding. One could augment the model with a consumption growth model. While we use the word "shocks", with consumption data one can examine how much of the variability that we document is unanticipated and how much is uninsured.[39] At a descriptive level, one could compare the family income variance profiles for specific groups to age profiles of wealth, which is a measure available in the PSID for some years since 1984. One could examine whether greater variability in the level and first difference of family income translate into higher wealth stocks, in keeping with a precautionary savings motive. Such work might provide guidance on how the cohort and gender differences we study have affected economy-wide trends in consumption and savings as well as inequality.

[38] Blundell et al (Forthcoming) use US tax data to estimates of earnings volatility over the lifecycle and over time for men and women. See footnote 8 for additional references.

[39] See Blundell, Pistaferri, and Preston (2008), Guvenen and Smith (2014), Blundell, Graber, and Mogstad (2015), and Blundell, Pistaferri, and Saporta-Eksten (2016).

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Table 1: Regressions of Family Income and Earnings on Education, Unobserved Variables, and Spouse Variables Using Simulated Data

		Cohort 35-44						**Cohort 64-74**					
		Male			Female			Male			Female		
Explanatory Variable	Dependant Variable	All (1a)	Married (2a)	Married (3a)	All (4a)	Married (5a)	Married (6a)	All (1b)	Married (2b)	Married (3b)	All (4b)	Married (5b)	Married (6b)
$EDUC$	family income	0.291	0.275	0.208	0.298	0.287	0.095	0.268	0.188	0.130	0.253	0.185	0.072
	earnings	*0.340*	*0.336*	*0.338*	*0.396*	*0.338*	*0.361*	*0.372*	*0.182*	*0.339*	*0.352*	*0.320*	*0.331*
μ	family income	0.264	0.260	0.240	0.171	0.147	0.063	0.266	0.247	0.208	0.227	0.192	0.123
	earnings	*0.345*	*0.344*	*0.344*	*0.228*	*0.204*	*0.218*	*0.363*	*0.371*	*0.364*	*0.319*	*0.305*	*0.328*
η	family income	0.098	0.095	0.095	0.055	0.034	0.031	0.088	0.078	0.079	0.086	0.056	0.060
	earnings	*0.138*	*0.137*	*0.137*	*0.143*	*0.129*	*0.129*	*0.132*	*0.140*	*0.134*	*0.178*	*0.176*	*0.176*
ν	family income	0.027	0.022	0.022	0.074	0.063	0.062	0.112	0.032	0.058	0.120	0.066	0.088
	earnings	*0.085*	*0.074*	*0.074*	*0.498*	*0.538*	*0.538*	*0.288*	*0.118*	*0.219*	*0.522*	*0.422*	*0.556*
ω	family income	0.219	0.214	0.213	0.091	0.057	0.054	0.211	0.194	0.182	0.150	0.110	0.106
	earnings	*0.315*	*0.314*	*0.314*	*0.208*	*0.188*	*0.189*	*0.318*	*0.332*	*0.321*	*0.283*	*0.268*	*0.280*
ω^h	family income	0.177	0.173	0.172	0.081	0.050	0.049	0.158	0.140	0.144	0.133	0.091	0.095
	earnings	*0.243*	*0.243*	*0.243*	*0.222*	*0.205*	*0.205*	*0.235*	*0.243*	*0.239*	*0.280*	*0.277*	*0.277*
Spouse Variables													
$EDUC_s$	family income			0.097			0.242			0.141			0.183
	earnings			*-0.003*			*-0.029*			*-0.005*			*-0.021*
μ_s	family income			0.065			0.238			0.127			0.208
	earnings			*0.0003*			*-0.040*			*0.002*			*-0.047*
η_s	family income			0.033			0.097			0.062			0.081
	earnings			*0.001*			*0.001*			*-0.001*			*0.003*
ν_s	family income			0.061			0.033			0.085			0.051
	earnings			*0.001*			*0.002*			*0.002*			*-0.002*
ω_s	family income			0.054			0.220			0.109			0.187
	earnings			*0.001*			*-0.037*			*0.002*			*-0.048*
ω_s^h	family income			0.057			0.175			0.103			0.153
	earnings			*0.0002*			*0.001*			*0.001*			*0.002*

Note: The table reports regressions of log earnings or log family income per adult equivalent on the explanatory variables listed in the rows using data simulated from the model for age 26 to 50. Rows where earnings is the dependent variable are italicized. Columns 1a-6a are for the 1935-44 cohort. Columns 1b-6b are for the 1964-74 cohort. The other column headings indicate gender and marital status. All equations include birth year and a cubic in age. All explanatory variables are in standard deviation units for the specific gender-cohort-age group. The number of simulated observations is 1,107,500 for column 1a, 957,526 for 2a and 3a, 1,145,000 for 4a, 931,511 for 5a and 6a, 1,862,500 for 1b, 1,347,229 for 2b and 3b, 1,885,000 for 4b, and 1,339,997 for 5b and 6b.

Table 2: Variance of Family Income AE by Age

	Age					
	26	30	35	40	45	50
Men	0.46	0.53	0.56	0.57	0.58	0.62
	(0.012)	(0.015)	(0.017)	(0.019)	(0.020)	(0.024)
Women	0.59	0.61	0.62	0.61	0.62	0.69
	(0.044)	(0.018)	(0.016)	(0.017)	(0.018)	(0.025)

Note: This table displays, by age and gender, the (simulated) variance in log family income per adult equivalent averaged across the three cohorts. Standard errors are calculated using 500 bootstrap samples. Family income per adult equivalent is equal to family income divided by the number of adult equivalents in the household. A household's adult equivalents are equal to $1 + 0.7 * Married + 0.5 * \#kids$.

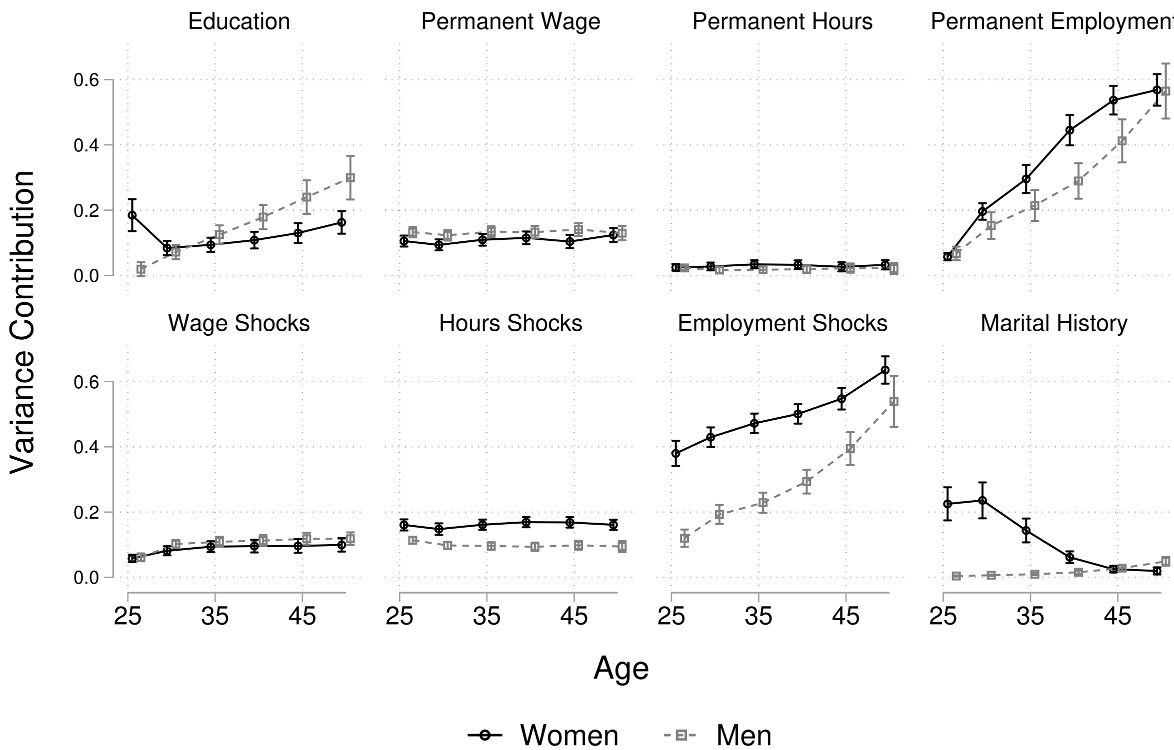
Figure 1: Contributions of Permanent Characteristics and Own Shocks to the Variance of Family Income AE by Age

Note: This figure displays the contribution of different model components to the variance in family income per adult equivalent at ages 26, 30, 35, 40, 45, and 50. 90% confidence intervals are calculated using 500 bootstrap samples. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Family income per adult equivalent is equal to family income divided by the number of adult equivalents in the household. A household's adult equivalents are equal to $1 + 0.7 * Married + 0.5 * \#kids$.

Figure 2: Contributions of Spouse Shocks to the Variance of Family Income AE by Age

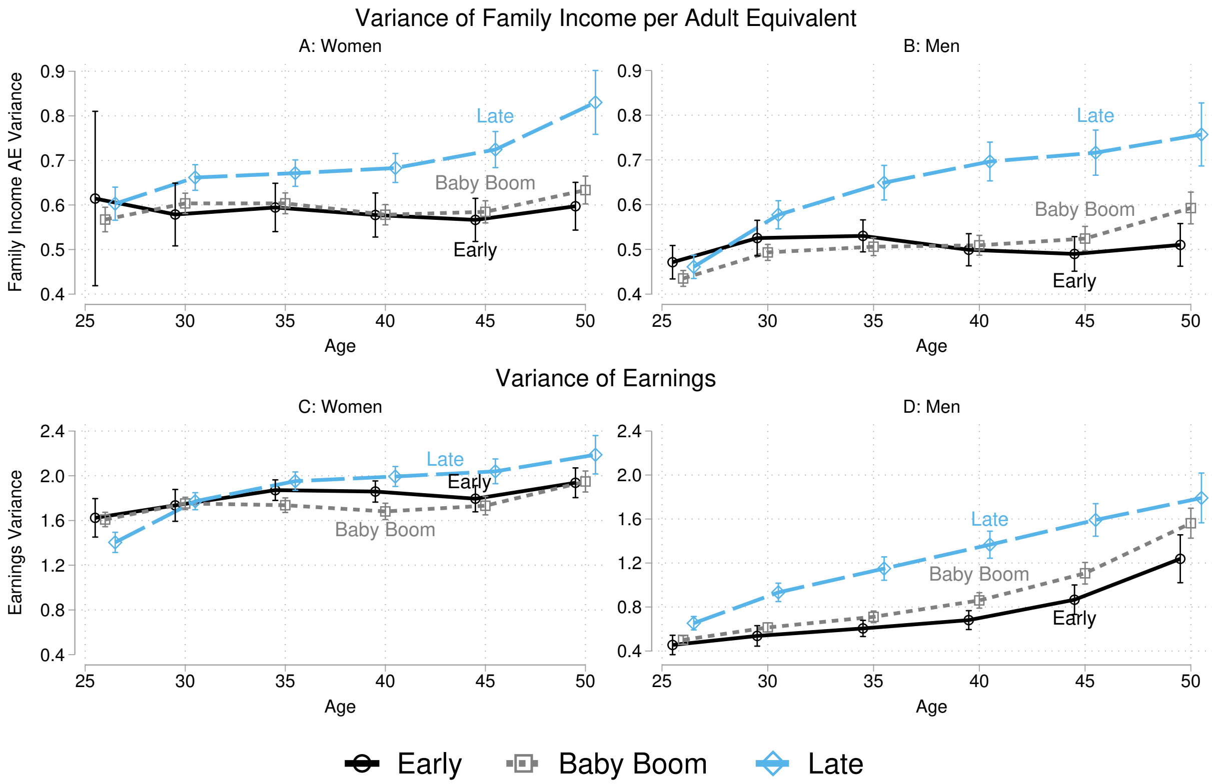
Note: This figure displays the contribution of different model components to the variance in family income per adult equivalent at ages 26, 30, 35, 40, 45, and 50. 90% confidence intervals are calculated using 500 bootstrap samples. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Family income per adult equivalent is equal to family income divided by the number of adult equivalents in the household. A household's adult equivalents are equal to $1 + 0.7 * Married + 0.5 * \#kids$.

Figure 3: Contributions to the Variance of Earnings by Age



Note: This figure displays the contribution of different model components to the variance in earnings at ages 26, 30, 35, 40, 45, and 50. 90% confidence intervals are calculated using 500 bootstrap samples. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Family income per adult equivalent is equal to family income divided by the number of adult equivalents in the household. A household's adult equivalents are equal to $1 + 0.7 * Married + 0.5 * \#kids$.

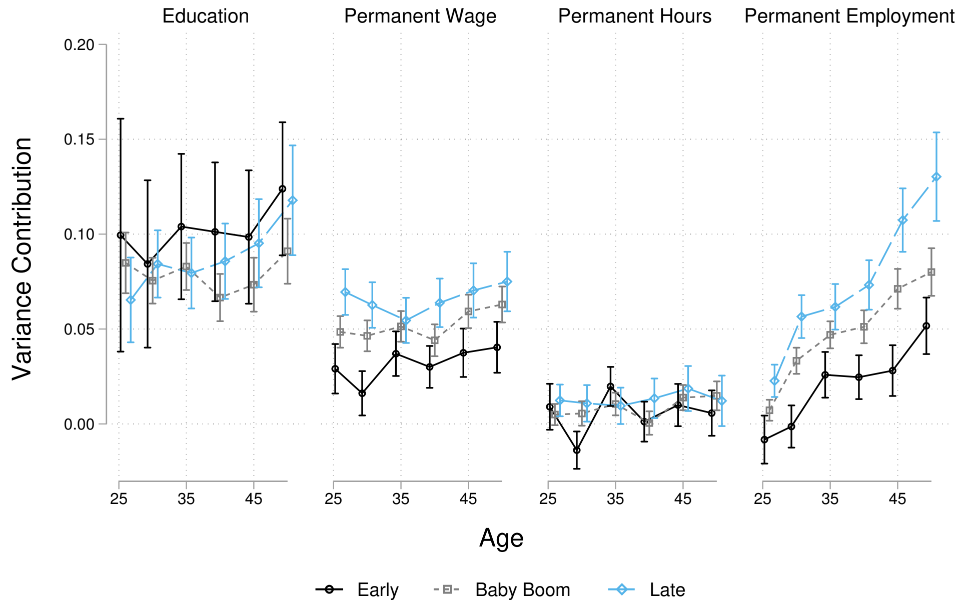
Figure 4: Variances by Age and Birth Cohort



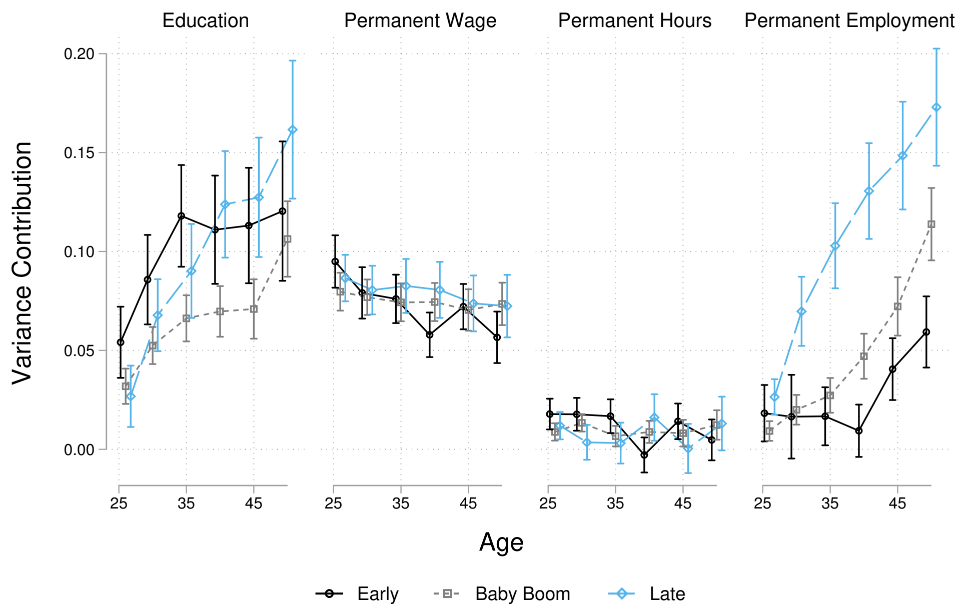
Note: This figure displays, by birth cohort, the (simulated) variance of family income per adult equivalent and earnings at ages 26, 30, 35, 40, 45, and 50. Early, baby boom, and late cohorts correspond to birth years 1935–44, 1945–62, and 1964–74, respectively. 90% confidence intervals are calculated using 500 bootstrap samples.

Figure 5: Contributions to the Variance of Family Income AE by Cohort: Permanent Characteristics

Panel A: Women



Panel B: Men



Note: This figure displays, by birth cohort, the contribution of different model components to the variance in family income per adult equivalent at ages 26, 30, 35, 40, 45, and 50. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Early, baby boom, and late cohorts correspond to birth years 1935–44, 1945–62, and 1964–74, respectively. 90% confidence intervals are calculated using 500 bootstrap samples.

Figure 6: Contributions to the Variance of Family Income AE by Cohort: Own Shocks

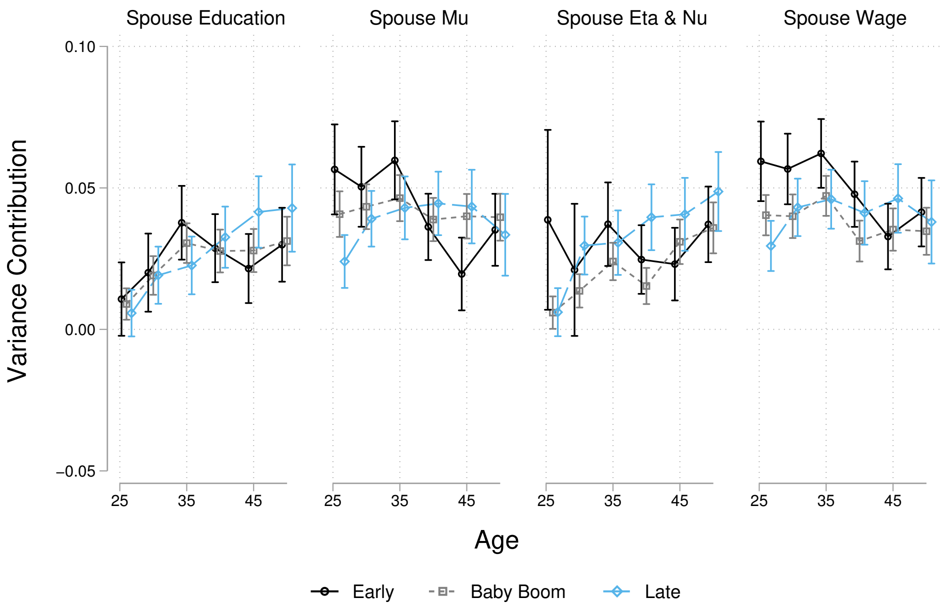
Panel A: Women

Panel B: Men

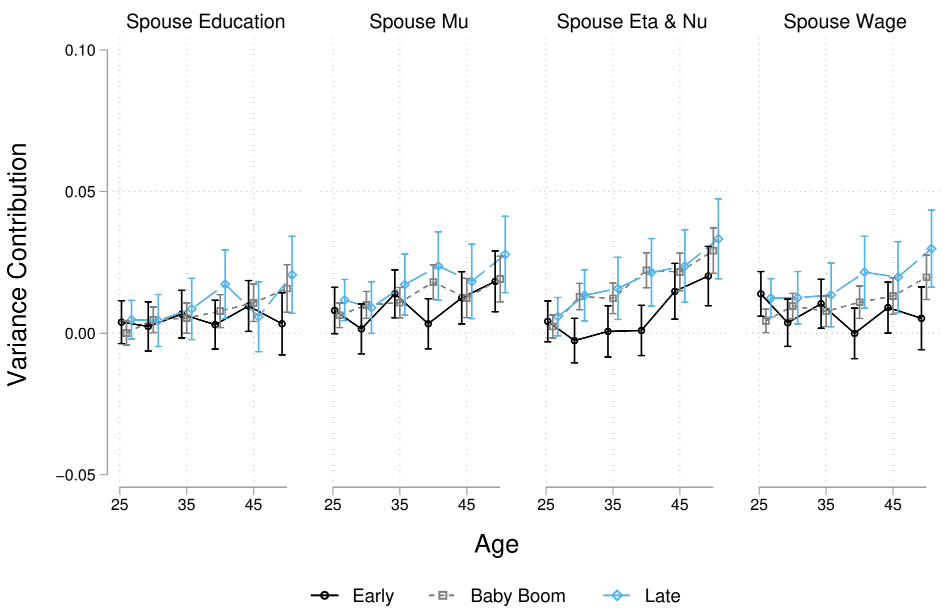
Note: This figure displays, by birth cohort, the contribution of different model components to the variance in family income per adult equivalent at ages 26, 30, 35, 40, 45, and 50. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Early, baby boom, and late cohorts correspond to birth years 1935–44, 1945–62, and 1964–74, respectively. 90% confidence intervals are calculated using 500 bootstrap samples.

Figure 7: Contributions to the Variance of Family Income AE by Cohort: Spouse Shocks

Panel A: Women

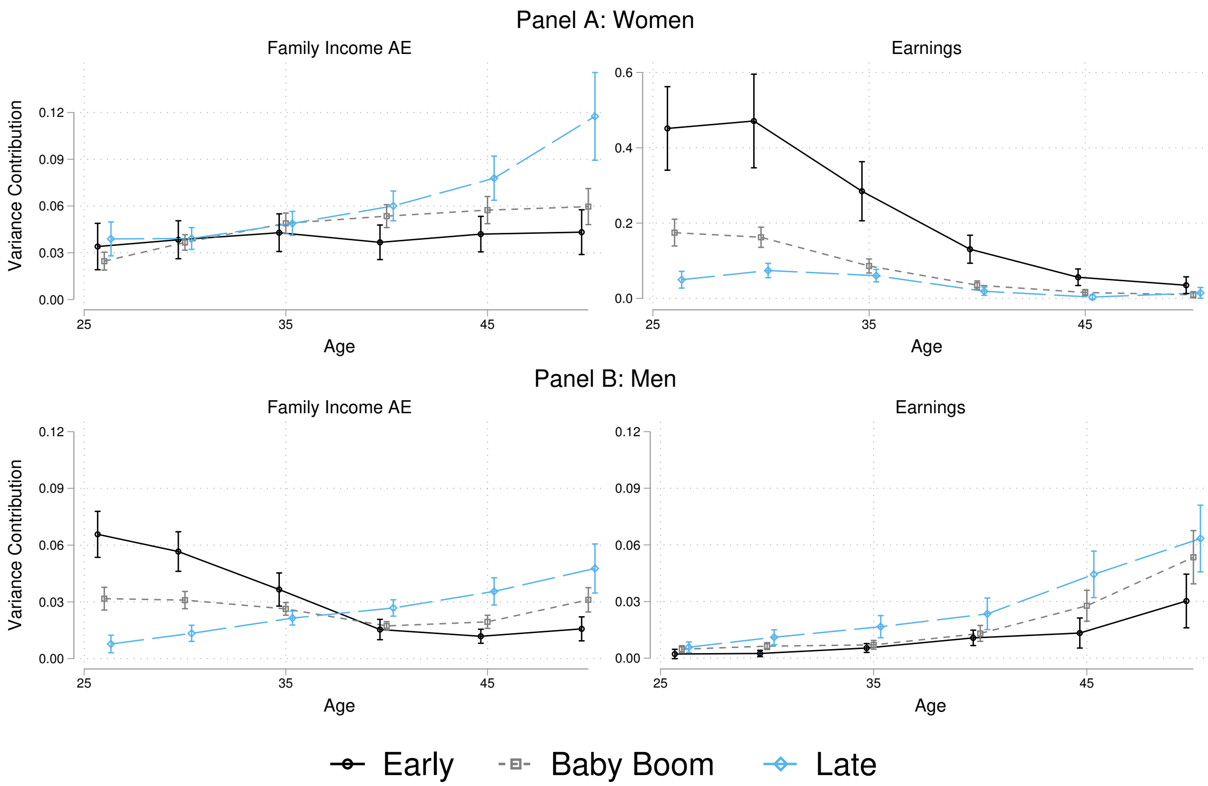


Panel B: Men



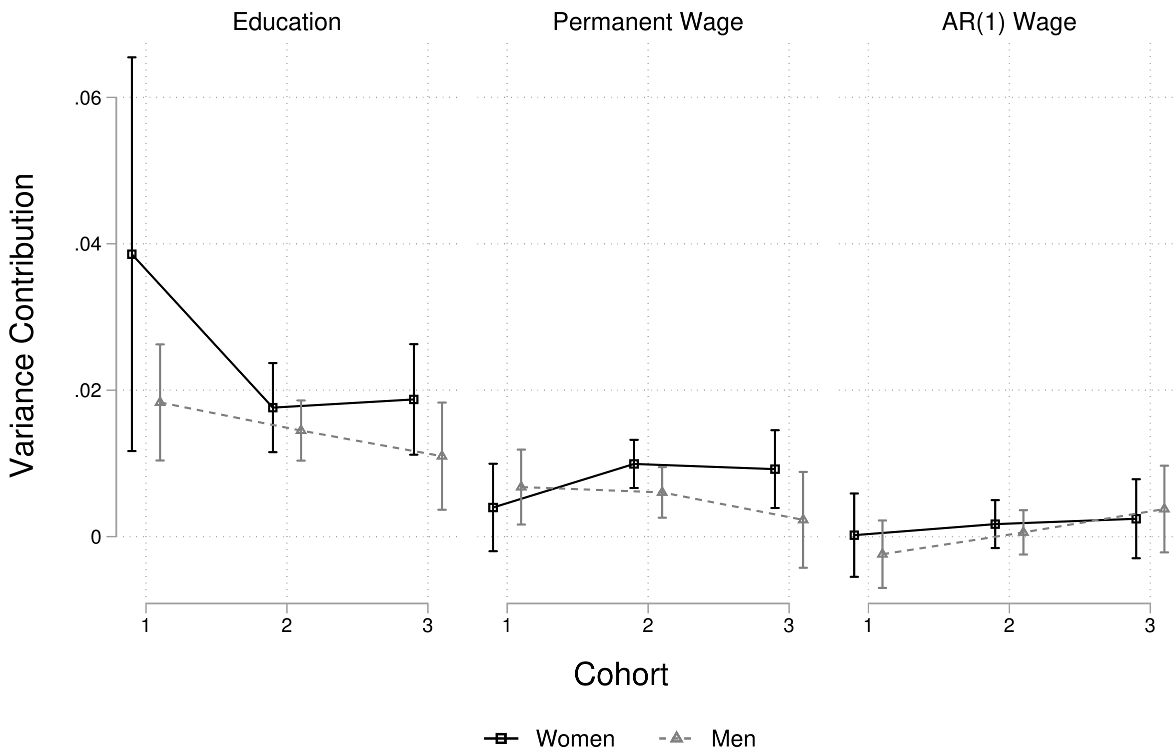
Note: This figure displays, by birth cohort, the contribution of different model components to the variance in family income per adult equivalent at ages 26, 30, 35, 40, 45, and 50. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Early, baby boom, and late cohorts correspond to birth years 1935–44, 1945–62, and 1964–74, respectively. 90% confidence intervals are calculated using 500 bootstrap samples.

Figure 8: Contributions of Marital History to the Variance of Family Income AE and Earnings



Note: This figure displays, by birth cohort, the contribution of marital history to the variance in family income per adult equivalent and earnings at ages 26, 30, 35, 40, 45, and 50. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Early, baby boom, and late cohorts correspond to birth years 1935–44, 1945–62, and 1964–74, respectively. 90% confidence intervals are calculated using 500 bootstrap samples. Note the very different scale used in the graph for women's earnings.

Figure 9: Contributions of Marital Sorting to the Variance of Family Income AE by Cohort



Note: This figure displays for each cohort the average contribution (across all six target ages) of marital sorting on education, permanent wage, and the AR(1) wage component to the variance in family income per adult equivalent and earnings. See Section 5.4 for a description of the variance decomposition methodology. The cohorts are presented in order: early (1), baby boom (2), and late (3) cohorts. These correspond to birth years 1935–44, 1945–62, and 1964–74, respectively.

Earnings, Marriage, and the Variance of Family Income by Age, Gender, and Cohort

Online Appendix

Joseph G. Altonji, Daniel Giraldo-Páez, Disa Hynsjö, and Ivan Vidangos

Supplemental Material. For Online Publication Only

Appendix Table of Contents

Appendix A Data Appendix

In this Appendix, we give an explanation of the data and its construction. We intend for it to be largely self-contained. This section is also part of the Appendix for AGHV. Appendix Tables A.1a-A.1c provide summary statistics for the PSID sample by cohorts. All monetary variables are in 2012 dollars.

Appendix A.1 Sample Selection

Our study uses the 1970-2019 waves of the PSID, which refer to the calendar years 1969-2018. The analysis focuses on sample members of the PSID and their spouses. A sample member is someone who was in the initial PSID sample or was the child of a sample member. Non-sample members enter the PSID by marrying into a PSID household. They leave the PSID sample when they separate from a sample member. Critically for who gets asked which questions, for most of the PSID "head" referred to the man of the household, regardless of whether he was a sample member and "wife" was the woman. (This terminology was changed in 2017 to "Reference Person and spouse). In the early waves of the PSID, some questions were only asked about heads of household.

We restrict the analysis to the stratified random sample (SRC) and exclude Black sample members. We do not use observations with a sample member or spouse younger than 19 or older than 69, and the core of the analysis is of sample members aged 25 to 61 and their spouses. We begin at age 25 because many sample members younger than 25 are neither heads of household nor spouses, and many key variables are not collected for non-head singles. Because of sample size considerations, we use data for ages 23-27 when estimating models of initial conditions at age 25. For the most part, we exclude observations if the potential experience of the sample member or spouse is greater than 40.

Observations for a given person-year are used if the person has valid data on education. We include the self-employed. Although the number of observations used in estimating each equation in the model varies, 8,250 sample members play a role in our simulations.

Appendix A.2 Notation and Demographic Variables

Throughout this Appendix, the subscript i denotes the PSID sample member, the subscript t denotes calendar year, and the subscript s indicates that a variable refers to a spouse. We denote age as a_{it}. Education $(EDUC_i)$ is years of education, which we measure by its average when multiple reports are available. Potential experience (PE_{it}) is $a_{it} - max(EDUC_i, 9) - 6$. For monetary variables and work hours, lower case letters indicate logs and upper case letters denote levels. If we allow for measurement error in a variable in a model, we use a * superscript to distinguish the measured value from the true value.

Appendix A.3 Wages, Hours, and Earnings

Earnings $\left(EARN^*_{it}\right)$ are an individual's annual wages and salaries, bonuses, overtime, tips, commissions, income from professional practice or trade, additional labor income, and the labor portion of business income. The survey question that provides these data is asked every survey year. From the 2003 survey year on, this question was not just asked about the previous year's earnings, but also about the 2-year retrospective earnings. So, we have earnings every calendar year from 2001 to 2018 and are only missing earnings data for the calendar years 1997 and 1999. We converted all monetary variables to 2012 dollars using the U.S. Bureau of Economic Analysis, Personal consumption expenditures implicit price deflator [DPCERD3Q086SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DPCERD3Q086SBEA in July 2022..

We clean the raw earnings data. We set it to a floor of $1300, which corresponds to the earnings from a minimum wage of $6.50 and the hours minimum of 200 that we employ. We also censored earnings to increase by no more than 500% or decrease by more than 80% in any given year.

Hours $\left(HOURS^*_{it}\right)$ are annual hours worked in all jobs. This information is requested in each survey year about the previous calendar year. After the switch to a biennial interview, the PSID asked a 2-year retrospective annual hours question every survey year beginning in 2003. Annual hours data, then, is only missing for calendar years 1997 and 1999. We censor annual hours to have a maximum value of 4000.

The measured hourly wage $\left(WAGE^*_{it}\right)$ is calculated by dividing (cleaned) annual earnings by the top-censored measure of annual hours $\left(EARN^*_{it}/HOURS^*_{it}\right)$. As a result, this measure is unavailable when earnings are missing, hours are zero or missing, or in the calendar years 1997 and 1999.

Once we have constructed the hourly wage variable, we further censor the wages and hours. Annual hours are censored from below at 200, including when hours are zero. $WAGE_{it}^{*}$ is censored from below at the minimum federal wage in 1991, \$4.25, corrected for inflation (roughly \$6.50 in 2012 dollars). Note that we do not subsequently adjust PSID earnings to reflect the application of the wage floor. As result, $ln(EARN_{it}^{*})$ is sometimes below the sum of the logs of our PSID wage and hours measures.[40]

If $wage_{it}^{*}$ is higher than $ln(150)$ and the individual worked fewer than 1200 annual hours, we set the wage to missing. Otherwise, we censor the wage from above at $ln(150)$. We do not allow growth of wages of more than 500% or decreases of more than 80%.

Lastly, we impute missing wages using the following procedure. First, we fill it using $wage_{2it}^{*}$, which is the prediction from a regression of $ln\left(EARN_{it}^{*}/HOURS_{it}^{*}\right)$ on log reported hourly wage rate at the time of the survey, $EDUC_i$, and other explanatory variables, fully interacted with gender.[41] If a reported wage rate is not available, we set $wage_{it}^{*}$ to $wage_{3it}^{*}$, which is the predicted value from a gender-specific regression of $ln\left(EARN_{it}^{*}/HOURS_{it}^{*}\right)$ on the explanatory variables only.

Appendix A.4 Employment Status

Employment (E_{it}), unemployment (U_{it}), and nonparticipation (N_{it}) are measured in the calendar year. We define an individual as being out of the labor force if they had zero hours of work in that calendar year.[42] For unemployment, we use PSID questions regarding the number of hours of unemployment or whether the individual was unemployed in the previous year. Questions of this nature are asked in every survey year of the PSID about the previous calendar year. Specifically, from 1968 to 1975 heads were asked about hours lost to unemployment and strikes. Spouses (i.e. married women) were not asked questions about hours of unemployment in the previous year until 1975. From 1976 to 1993, heads and spouses were asked about hours lost to unemployment; from

[40] For example, if a PSID respondent reports \$1500 for annual earnings in 2012 (the based year of our price index) and 300 for hours, then we set the wage to the floor of \$6.50 rather than to \$5.00=1500/300 but do not adjust earnings. The log of our earnings measure (log(1500)) is less than sum of the logs of the hours and the wage measure (log(300) + log(6.5)). Note that $EARN_{it}^{*}$ is used to evaluate model fit but does not play a direct role in estimation of the model or in the model simulations or in the variance decompositions.

[41] The PSID asks individuals who are employed at the time of the survey for their current wage rate in their job. Because this is only available in survey years after 1997, we estimate the prediction equation using only data from before 1996 and without including a year polynomial in the specification.

[42] To construct the participation measure, we use reported hours before we censor hours from below at 200.

1994 to 2001 they were asked about whether they were unemployed or laid off in the previous year. Starting in the 2003 survey year, heads and spouses were asked in survey year t if they were ever unemployed in calendar year $t - 2$. So information about unemployment is available in all calendar years from 1969 to 2018 except for 1997 and 1999 for men and women and 1969-1973 for married (or cohabiting) women.

We define an individual as employed in a calendar year if they had positive hours of work and experienced no unemployment. In this way, the three employment statuses are mutually exclusive. Note that, as a result, we classify the small number of individuals who worked no hours in a calendar year but experienced unemployment as out of the labor force.

Appendix A.5 Marriage and Children

Marital status (MAR_{it}) is based on the PSID marriage variable that is made every survey and includes cohabitations lasting longer than one year. After 1997, we do not have PSID survey values for even-numbered years. We impute data for marital status using a variety of rules and additional PSID variables.

First, if the sample member's marital status remains the same across two adjacent survey years (and, if married, they are married to the same spouse), then we assume they had the same marital status in the intervening even-numbered year. When there is a change in marital status across odd-numbered years, we use the move-in/move-out information in the PSID to assign the year of marital status change. We do this in such a way as to match the PSID's own treatment of cohabitation in the marital status variable. For example, if a cohabitor began living in a household early in year t and by $t + 2$ the sample member is coded as "married," then we also code them as married in year $t + 1$, as by the time of a typical survey the cohabitor would have been living in the household for more than one year in $t + 1$. Likewise, we use move-out data to determine if a couple was married in the even-numbered year between a separation. We further supplement the remaining missing values of marital status by referring to the PSID marital history file.

Using the constructed sequence of marital status, we calculate the implied marriage duration $(MARDUR_{it})$. This is simple for those individuals who married after age 25. To determine the marital duration of those who are already married at age 25, we use the PSID questions about age at the start and end of the individual's first and second marriages. $MARDUR_{it}$ at age 25 is censored from above at 11, as the youngest possible age to report at first marriage is 14.

We use the PSID Childbirth and Adoption file to create the children variables. We use the birth years of the children in the childbirth and adoption file to build indicators for whether the individual has a child aged 0 to 1, 1 to 2, 2 to 3, etc., up to age 18. In most of our equations, we aggregate the age-specific indicators into counts of children aged between 0 and 5 $(CH05_{it})$, 6 and 12 $(CH612_{it})$, and 13 and 18 $(CH1318_{it})$. We sometimes use CH_{it} to refer to a vector of the three variables. In the marriage equation we use CH_VAR_{t-1}, which is an index of young children in $t-1$. It is the sum of an indicator for the presence of a child less than 1 year old and one-half of the sum of indicators for children aged 1, 2, 3, and 4.

Appendix A.6 Nonlabor Income, Family Income, and Adult Equivalence

Real nonlabor income (NLY_{it}) is the sum of head and spouse's taxable income and transfers received, minus head and spouse earnings. It is censored from below at $500 2012 dollars. The questions for taxable income and transfers are never asked about calendar year $t-2$ in survey year t. As a result, we are unable to obtain information on nonlabor income for odd years after 1996. To accommodate this, we model nly_{it} as being a function of contemporaneous variables and an autoregressive error. We only use data from before 1997 to estimate the parameters of the autoregressive error process.

Real family earnings $(FAMEARN_{it})$ is the sum of the sample member's earnings and the spouse's earnings (if present). Real family income, Y_{it}, is the sum of $FAMEARN_{it}$ and uncensored nonlabor income of the head or the head and wife. It is censored from below at $2000 in 2012 dollars.

The variables AE_{it} and ae_{it} are the level and log of the OECD's adult equivalence scale.[43] The variables Y_AE_{it} and its log y_ae_{it}, and other variables with the AE or ae suffix are on an adult-equivalent basis. When simulating and assessing fit, we only consider the head, spouse, and children of the PSID sample members who are under 18 when creating AE_{it} to avoid having to model the presence of other adults and children of others.

[43]The scale is: $1 + 0.7\,(\#adults - 1) + 0.5 * (\#children)$

Table A.1a: PSID Data Summary Statistics by Gender (Birth Cohort 35-44)

	Men		Women	
	Mean	Sd	Mean	Sd
Age	42.75	9.189	42.72	9.022
Education	13.08	2.510	12.69	2.148
Potential Experience	23.53	9.189	23.95	9.043
Log Reported Wage	3.105	0.469	2.642	0.493
Wage $(wage^*)$	3.118	0.551	2.655	0.501
Wage $\|Earnings/Hours$	3.118	0.564	2.677	0.559
Log Hours	7.602	0.563	6.618	1.036
Log Earnings	10.61	0.996	8.987	1.468
Employed	0.941	0.233	0.663	0.472
Unemployed	0.020	0.142	0.012	0.108
Nonparticipation	0.037	0.190	0.324	0.467
Married	0.871	0.333	0.816	0.386
Marriage Duration $\|Married$	14.86	10.97	15.72	12.04
Children Aged 0-5	0.224	0.536	0.155	0.446
Children Aged 6-12	0.528	0.836	0.465	0.814
Children Aged 13-18	0.411	0.699	0.430	0.728
Log Unearned Income	7.698	1.682	7.903	1.710
Log Family Income	11.09	0.649	11.03	0.708
Log Family Income AE	10.35	0.721	10.33	0.741
Level of Family Income	79881	56103	77985	60683
Level of Family Income AE	40566	34043	40207	33690
Log Family Transfers	6.747	1.166	6.992	1.373
Spouse Age $\|Married$	39.53	9.531	45.36	9.777
Spouse Education $\|Married$	12.67	1.935	12.98	2.726
Spouse Potential Experience $\|Married$	20.82	9.564	26.19	10.03
Spouse Log Reported Wage $\|Married$	2.602	0.470	3.118	0.485
Spouse Wages $\|Married$	2.782	0.527	3.101	0.591
Spouse Wages $\|Earnings/Hours, Married$	2.625	0.545	3.141	0.601
Spouse Log Earnings $\|Married$	8.770	1.442	10.56	1.141
Spouse Log Hours $\|Married$	6.482	1.029	7.573	0.629
Spouse Employed $\|Married$	0.630	0.483	0.933	0.25
Spouse Unemployed $\|Married$	0.008	0.089	0.017	0.128
Spouse Nonparticipation $\|Married$	0.361	0.479	0.050	0.217

Table A.1b: PSID Summary Statistics by Gender (Birth Cohort 45-62)

	Men		Women	
	Mean	Sd	Mean	Sd
Age	41.49	9.982	41.29	9.937
Education	13.84	2.118	13.44	2.094
Potential Experience	21.63	9.998	21.83	9.951
Log Reported Wage	3.052	0.493	2.743	0.501
Wage $(wage^*)$	3.147	0.601	2.786	0.550
Wage $\|Earnings/Hours$	3.144	0.625	2.805	0.592
Log Hours	7.534	0.638	6.918	0.966
Log Earnings	10.56	1.080	9.434	1.435
Employed	0.917	0.275	0.754	0.430
Unemployed	0.032	0.175	0.026	0.158
Nonparticipation	0.050	0.216	0.217	0.412
Married	0.773	0.418	0.726	0.446
Marriage Duration $\|Married$	10.61	10.36	10.49	10.69
Children Aged 0-5	0.238	0.541	0.214	0.517
Children Aged 6-12	0.386	0.700	0.409	0.725
Children Aged 13-18	0.270	0.568	0.305	0.600
Log Unearned Income	7.618	1.616	7.743	1.634
Log Family Income	11.09	0.759	10.98	0.802
Log Family Income AE	10.43	0.763	10.33	0.796
Level of Family Income	84791	67310	78169	62849
Level of Family Income AE	44829	37758	40651	32994
Log Family Transfers	6.899	1.266	7.105	1.386
Spouse Age $\|Married$	39.84	10.23	43.04	10.40
Spouse Education $\|Married$	13.66	2.007	13.64	2.289
Spouse Potential Experience $\|Married$	20.23	10.13	23.38	10.46
Spouse Log Reported Wage $\|Married$	2.730	0.500	3.069	0.488
Spouse Wages $\|Married$	2.901	0.563	3.119	0.584
Spouse Wages $\|Earnings/Hours, Married$	2.803	0.595	3.160	0.605
Spouse Log Earnings $\|Married$	9.222	1.488	10.55	1.129
Spouse Log Hours $\|Married$	6.760	1.008	7.519	0.685
Spouse Employed $\|Married$	0.725	0.446	0.919	0.273
Spouse Unemployed $\|Married$	0.017	0.129	0.023	0.150
Spouse Nonparticipation $\|Married$	0.256	0.437	0.057	0.231

Table A.1c: PSID Summary Statistics by Gender (Birth Cohort 64-74)

	Men		Women	
	Mean	Sd	Mean	Sd
Age	36.96	7.379	37.01	7.498
Education	13.61	2.049	13.90	1.934
Potential Experience	17.37	7.642	17.12	7.698
Log Reported Wage	2.983	0.479	2.811	0.495
Wage $(wage^*)$	3.108	0.601	2.852	0.559
Wage $\|Earnings/Hours$	3.111	0.629	2.878	0.610
Log Hours	7.558	0.634	7.019	0.952
Log Earnings	10.53	1.151	9.682	1.434
Employed	0.919	0.273	0.779	0.414
Unemployed	0.035	0.187	0.030	0.173
Nonparticipation	0.043	0.206	0.187	0.391
Married	0.714	0.451	0.689	0.462
Marriage Duration $\|Married$	6.879	7.227	7.276	7.748
Children Aged 0-5	0.324	0.595	0.307	0.583
Children Aged 6-12	0.467	0.736	0.536	0.768
Children Aged 13-18	0.236	0.528	0.321	0.601
Log Unearned Income	7.361	1.514	7.488	1.547
Log Family Income	11.08	0.833	11	0.860
Log Family Income AE	10.45	0.782	10.34	0.823
Level of Family Income	88247	74216	81880	68190
Level of Family Income AE	45989	38878	41281	33092
Log Family Transfers	6.861	1.182	7.099	1.335
Spouse Age $\|Married$	36.15	7.788	39.18	8.137
Spouse Education $\|Married$	14.03	1.949	13.75	2.105
Spouse Potential Experience $\|Married$	16.15	7.922	19.49	8.329
Spouse Log Reported Wage $\|Married$	2.795	0.493	3.045	0.474
Spouse Wages $\|Married$	2.954	0.550	3.132	0.579
Spouse Wages $\|Earnings/Hours, Married$	2.894	0.591	3.174	0.597
Spouse Log Earnings $\|Married$	9.592	1.465	10.60	1.108
Spouse Log Hours $\|Married$	6.948	0.986	7.558	0.615
Spouse Employed $\|Married$	0.771	0.419	0.931	0.252
Spouse Unemployed $\|Married$	0.023	0.149	0.020	0.143
Spouse Nonparticipation $\|Married$	0.206	0.404	0.046	0.209

Appendix B Model Estimates

In this section, we display the full estimates of the model. We also provide more detail on some of the estimation procedures. This section overlaps very heavily with the AGHV Appendix.

B.1 Estimating the distribution of employment, marriage, and number of children at age 25

For a simulated individual with a given education, gender, and birth cohort, we need to draw the following initial conditions, or values at age 25: initial labor market status, initial marital status, initial marital duration, and initial number of children. To do so, we break up the PSID sample into education, gender, and birth cohort combinations and then, for each of the combinations, we estimate the joint distributions of the initial variables in the PSID data. Then, when simulating an individual, we draw her initial conditions from the joint distribution that corresponds to her education-gender-cohort combination.

In the combinations, we allow for two types of education, five cohorts, and two genders, leading to 20 possible combinations. The education types are those with at most 12 years of schooling and those with more than 12 years. The birth cohort groups are 1935–1944, 1945–1953, 1954–1962, 1963–1974, and 1975–1983.

For each of the combinations, we estimate the joint distribution of initial labor market status (N, E, or U), initial marital status, initial marital duration, and initial number of children using all individuals with that education-gender-cohort combination in the PSID. We use only one observation per person, typically the age 25 observation for individuals in that education-gender-cohort combination. We use age 23 (24) for persons who are last observed at age 23 (24) and use the age 26 (27) observation for persons first observed at age 26 (27).

Because of limitations in the data, we make a couple of adjustments for estimating some of the joint distributions. First, before 1974 women are generally missing employment status, as wives did not get asked in early PSID survey years if they had been unemployed in the previous year. This means that most women in the first cohort grouping (1935–1944) are missing unemployment measures at age 25, as are many women in the second cohort grouping (1945–1953). We impute these women's employment status using a multinomial logit model with marital status, marriage duration, an indicator for having kids, and number of children as the explanatory variables. We train this prediction model with the sample of women aged 25 born after 1944 with nonmissing unemployment statuses. For women in the 1945–1953 cohorts, this is the only adjustment we make to the data.

For women (and men) in the 1935–1944 cohort, we have to make an additional imputation. Because the PSID began in 1968, we do not observe (most) individuals in this cohort at age 25 (or even 27). As a result, in addition to using the employment status imputation for both men and women, we adopt additional procedures to establish number of kids, marital status, and marriage duration at age 25. For that, we turn to the PSID Marital History and Childbirth and Adoption File. Using these histories, we can look back and see whether the individual was married at age 25 and how many children he or she had at that age.

This imputation procedure runs into one difficulty. The PSID's Marital History file begins in 1985. Specifically, the PSID began asking sample members for their full marriage history in 1985. So there is a subset of sample members for whom this marital history data is missing because they no longer responded to the survey by 1985. We have reason to believe that this nonresponse group is systematically less likely to be married at age 25 than individuals in the 1935–1944 cohort that did make it long enough to respond to the marriage history questions, inflating our measure of marriage at age 25. To counter this, we reweight "married" observations downward (and "single" observations upward) so that the marriage rate of each gender-education combination for this cohort matches the marriage rate at age 25 for that gender-education group in the CPS-ASEC.

Finally, once we have drawn these initial conditions, to simulate we also need to specify the ages of the individual's children. To draw the ages, we estimate the joint probability of the possible combinations of ages of children given the number of children the person has. This estimation pools across cohorts. In estimating the age distribution of children, we prioritize the observation at age 25 in a similar fashion as we did above.

B.2 Estimating the variances of the wage error components

For men, we estimate γ_X^w and γ_{mar}^w by applying 2SLS to the equation

$$wage_{it}^* = X_{it}^w \gamma_X^w + LFS_{i,t-1}\gamma_{LFS}^w + MAR_{it}\gamma_{mar}^w + \mu_i + \omega_{it} + \varepsilon_{it}^w + \ me_{it}^w.$$

We use the deviations of MAR_{it} from individual means as an instrumental variable. The lagged unemployment variable, which for men is the sole element of the vector $LFS_{i,t-1}$, is excluded.

Define $e_{it}^w = \mu_i + \omega_{it} + \varepsilon_{it}^w + me_{it}^w$. Using (3) for men,

$$e_{it}^{w}-\gamma_{U}^{\omega}U_{i,t-1}=\rho^{\omega}e_{i,t-1}^{w}+(1-\rho^{\omega})\mu_{i}+u_{it}^{\omega}+(\varepsilon_{it}^{w}+me_{it}^{w})-\rho^{\omega}\left(\varepsilon_{it}^{w}+me_{i,t-1}^{w}\right). \quad (8)$$

We estimate the parameters of the above equation by 2SLS after replacing e_{it}^{w} and ρe_{it}^{w} with the residuals from the equation for $wage_{it}^{*}$. The instruments are the deviations of $U_{i,t-1}$ from individual means and $(e_{i,t-2}^{w}-e_{i,t-3}^{w})$ and $(e_{i,t-3}^{w}-e_{i,t-4}^{w})$. Define the quasi difference qe_{it}^{w} as

$$\begin{aligned} qe_{it}^{w} &\equiv e_{it}^{w}-\gamma_{U}^{\omega}U_{i,t-1}-\rho^{\omega}e_{i,t-1}^{w} && (9)\\ &= (1-\rho^{\omega})\mu_{i}+u_{it}^{\omega}+(\varepsilon_{it}^{w}+me_{it}^{w})-\rho^{\omega}\left(\varepsilon_{it}^{w}+me_{i,t-1}^{w}\right), && (10)\end{aligned}$$

where the second equation follows from (3).

Because u_{it}, ε_{it}^{w}, and me_{it}^{w} are serially uncorrelated, $Cov(qe_{it}^{w},e_{i,t-k}^{w})=(1-\rho)\sigma_{\mu^{w}}^{2}$ for any $k=2,3,....$ We average over values for $k=2$ to 6, so the moment condition is

$$\sigma_{\mu^{w}}^{2}=\frac{1}{5(1-\rho)}\sum_{k=2}^{6}cov(qe_{it}^{w},e_{i,t-k}).$$

To obtain $\hat{\sigma}_{\mu^{w}}^{2}$, we evaluate the above moment condition after first replacing e_{it}^{w} with the 2SLS residuals $\hat{e}_{it}^{w}$ and replacing qe_{it}^{w} with $\hat{e}_{it}^{w}-\hat{\gamma}_{U}^{\omega}U_{i,t-1}-\hat{\rho}^{\omega}\hat{e}_{i,t-1}^{w}$.

Next, we obtain $\hat{\sigma}_{me^{w}}^{2}$. To do so, we leverage the PSID reported wage measure. Denote the reported wage as

$$wage_{it}^{**}=X_{it}^{w}\gamma_{X}^{w}+MAR_{it}\gamma_{mar}^{w}+\mu_{i}+\omega_{it}+\varepsilon_{it}^{w**}+me_{it}^{w**}.$$

We assume that me_{it}^{w**} and me_{it}^{w} are uncorrelated with each other as well as with all the other terms. They are also allowed to have different variances. Further, we assume that $\varepsilon_{it}^{w}=\varepsilon_{it}^{w**}$ and that ω_{it} and ε_{it}^{w} are covariance stationary.

Consider the regression of $wage_{it}^{*}$ on $wage_{i,t-1}^{*}$. Let b_{1OLS} be the probability limit of the coefficient of this regression. Further, let b_{1IV} be the probability limit of the corresponding IV regression using $wage_{i,t-1}^{**}$ as the instrument for $wage_{i,t-1}^{*}$. Then it can be shown that

$$var\left(me_{it}^{w}\right)=\left(1-\frac{b_{1OLS}}{b_{1IV}}\right)var\left(wage_{it}^{*}\right).$$

We estimate $var\left(me_{it}^{w}\right)$ by replacing the above measures with their sample analogs.

For the rest of the variances, we exploit the following relationships. First note that

$$cov\left(e_{it},e_{i,t-1}\right)=\mu_{i}+\rho^{w}var\left(\omega_{it}\right).$$

We can therefore use the sample analog of $cov\left(e_{it},e_{i,t-1}\right)$ to estimate $var\left(\omega_{it}\right)$. With that in hand, we can estimate $var\left(u_{it}^{w}\right)$ using the relationship

$$var\left(u_{it}^{w}\right) = \left(1 - [\rho^{w}]^{2}\right) var\left(\omega_{it}\right).$$

Finally, we can use that the mean square error of the wage regression is equal to

$$var\left(\mu_{i}\right) + var\left(\omega_{it}\right) + var\left(me_{it}\right) + var\left(\varepsilon_{it}^{w}\right)$$

to estimate $var\left(\varepsilon_{it}^{w}\right)$.

The procedure is the same for women, except that the model of $wage_{it}^{*}$ includes lags of E_{it} and U_{it}, and these are not included in the wage residual. The instruments are deviations from individual means of MAR_{it} and the lags of E_{it} and U_{it}. Note that all wage model parameters are gender-specific.

B.3 Estimation of the Hours Model

We instrument for the wage using a wage measure that is constructed using the reported wage if available or the demographics-based wage if not. We allow for the possibility that MAR_{it}, children, and interaction terms are related to η_i by using the deviations from the individual means of the corresponding variables as instruments.

We estimate σ_{η}, ρ^{h}, and $\sigma_{\varepsilon^{h}}$ using a method of moments procedure. It involves the autocovariances of the hours residuals at lags 0 to 7. It accounts for the assumed value of 0.122 for σ_{me}^{h} (see Appendix B.5). We assume that η_i has a truncated normal distribution with a minimum and maximum of $-1.64\sigma_{\eta_x}$ and $1.64\sigma_{\eta_x}$, where σ_{η_x} is chosen so that the variance of the truncated normal matches the method of moments estimate of σ_{η}^{2}. We use the truncated normal to reduce the influence of extremely large values of the permanent heterogeneity term in model simulations. Additionally, we constrain the estimation so that σ_{η}^{2} is at least 0.004 to avoid numerical problems.

B.4 Estimation of Sorting Parameters for Wage Error Components

Following AGHV, we use the method of moments to fit $\gamma_{m}^{\mu_s}$ and $\gamma_{m}^{\omega_s}$ to the covariances of the wage residuals of the sample member and the spouse at various leads and lags during the marriage. We impose the restriction $\gamma_{m}^{w_s} \equiv \gamma_{m}^{\mu_s} = \gamma_{m}^{\omega_s}$. We allow all parameters to depend on whether $B_i \leq 1962$. Consider the case of male sample members. Let $wres_{it}^{*}$ and $wres_{it}^{s*}$ denote the composite error term for the male and female specifications of (2):

$$wres_{it}^{*} \equiv \mu_i + \omega_{it} + \varepsilon_{it}^{w} + me_{it}^{w}$$

$$wres_{it}^{s*} \equiv \mu_i^s + \omega_{it}^s + \varepsilon_{it}^{ws} + me_{it}^{ws}.$$

Given the process for ω_{it} and ω_{it}^s and using more explicit notation to identify the gender of the sample member and the spouse, we have

$$cov(wres^*_{i,t_0(i)+j-1}, wres^{s*}_{i,t_0(i)+k}) = (\gamma_m^{w_s})Var(\mu_{mi}) + \gamma_m^{w_s}(\rho_m^{\omega})^{j+1}(\rho_f^{\omega})^{k-1}Var(\omega_{mit_0-1}), \quad (11)$$

where $t_{0(i)}$ is the year that i married and $j = 0, ..J$ and $k = 1...K$ and j and k are marriage duration in year $t_{0(i)} + j$ or $t_{0(i)} + k$, respectively. We estimate $Var(\omega_{mit_0-1})$ by estimating $Var(wres^*_{it})$ for men and subtracting $Var(\mu_{mi})$, $Var(me^w_{it})$, and $Var\left(\varepsilon^w_{it}\right)$. We obtain ρ^{ω}_m and ρ^{ω}_f from the estimation of the wage equation. We replace $cov(wres^*_{i,t_0(i)+j-1}, wres^*_{si,t_0(i)+k})$ in (11) with sample estimates and estimate $\gamma^{w^s}_{m\mu}$ by weighted nonlinear least squares. We set J and K to 15, and weight the covariances by the number of observations used to estimate them. In the bootstrap procedure, we estimate $Var(\omega_{mit_0-1})$ for each bootstrap sample.

The procedure for female sample members (and male spouses) is the same, except that the equations for $wres^*_{it}$ and $wres^{s*}_{it}$ are switched. We constrain the estimates such that their values imply a strictly positive variance of $\tilde{\omega}_{sit_0}$. The estimates are in Appendix Table B.11.

B.5 Choice of Measurement Error Variance Values

We set σ^h_{me} to 0.122. For men, this implies that measurement error accounts for 12% of the variance of $hours^*_{it}$ when $hours^*_{it}$ exceeds the floor of $\ln(200)$. For women the value is 6%. Reducing (increasing) the value of σ^h_{me} would increase (reduce) the contribution of i.i.d. hours shocks to the variance of earnings and hours in a given year but would have little effect on decompositions of lifetime hours, earnings, family earnings, or family income. The changes would not affect any impulse response functions that we report. (For how we set σ^w_{me}, see Appendix B.2.)

Table 1: Table B.1a: Log Wage Model

	(1) Men	(2) Women
Married	0.04991***	-0.00468
	(0.00962)	(0.01611)
Education	0.13547***	0.13385***
	(0.00491)	(0.00549)
Potential Experience	0.01583***	0.01172***
	(0.00088)	(0.00129)
Potential Experience^2	-0.00087***	-0.00088***
	(0.00007)	(0.00011)
Potential Experience^3	0.00002***	0.00002***
	(0.00000)	(0.00001)
Education*Potential Experience	0.00138***	0.00024
	(0.00029)	(0.00036)
Education*Potential Experience^2	-0.00011***	-0.00007***
	(0.00002)	(0.00003)
Year	0.00305***	0.00451***
	(0.00085)	(0.00110)
Year^2	0.00010***	0.00013***
	(0.00002)	(0.00005)
Year^3	-0.00001***	-0.00001***
	(0.00000)	(0.00000)
Cohort*Married		0.00179**
		(0.00090)
Cohort^2*Married		0.00002
		(0.00006)
Lag Participation		0.13668***
		(0.01220)
Lag Unemployed		-0.08046***
		(0.00854)
Second Lag Participation		0.09324***
		(0.01108)
Second Lag Unemployed		-0.07483***
		(0.00824)
Third Lag Participation		0.05958***
		(0.01078)
Female*Children 0-5		0.00540
		(0.01348)
Female*Children 6-12		-0.05501***
		(0.01018)
Female*Children 13-18		-0.05904***
		(0.01160)
Cohort*Female*Children 0-5		0.00349***
		(0.00110)

Cohort*Female*Children 6-12		-0.00024
		(0.00055)
Cohort*Female*Children 13-18		-0.00035
		(0.00055)
Cohort^2*Female*Children 0-5		-0.00015^{***}
		(0.00005)
Cohort^2*Female*Children 6-12		-0.00006^{*}
		(0.00003)
Cohort^2*Female*Children 13-18		-0.00007^{*}
		(0.00004)
Cohort^2		-0.00005
		(0.00005)
Constant	2.96221^{***}	2.45566^{***}
	(0.01452)	(0.02736)
R-squared	0.22	0.28
Observations	62414	42270

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.1a displays selected parameter estimates for the wage level model, for men and women. Standard errors (in parentheses) are clustered at the individual level. Education and potential experience are normalized so that the coefficient on female and education are for an individual of age 34 with 12 years of education and 16 years of potential experience. Birth cohort is normalized to be 0 at 1960. For both men and women, we instrument marital status with the deviations of marital status from individual means. For women, we instrument the lags of employment and unemployment with deviations from individual means. The models are estimated using individuals aged 23-61. Only observations where either earnings/hours or the predicted wage based on the reported wage are available are used. Predicted wages based only on demographics are not used.

Table B.1b: Log Wage Error Process

	Men	Women
ρ^{ω}	0.810***	0.770***
	(0.027)	(0.044)
Lag Unemployed	-0.109***	
	(0.009)	
Constant	0.017***	0.014***
	(0.002)	(0.003)
σ_{μ}	0.350***	0.331***
	(0.011)	(0.013)
$\sigma_{u^{\omega}}$	0.183***	0.186***
	(0.007)	(0.010)
$\sigma_{\varepsilon^{w}}$	0.123***	0.074***
	(0.011)	(0.022)
$\sigma_{\omega_{25}}$	0.125***	0.159***
	(0.031)	(0.027)
$\sigma_{me^{w}}$	0.234***	0.244***
	(0.004)	(0.004)
R-squared	0.56	0.51
Observations	40160	23315

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.1b displays the estimated regression coefficients and standard deviation parameters of the wage error process. For men, we model the wage error as an AR(1) process including lag unemployment. For women, lags of employment and unemployment are included in the wage level model reported in Table B.1a rather than in the wage error process. See Section 3.2.1. The table displays the estimated standard deviation of unobserved heterogeneity, σ_{μ}, the standard deviation of the innovation in ω, σ_{u}^{ω}, the standard deviation of the i.i.d. shock to wage ε^{w}, the standard deviation of the initial draw of ω, $\sigma_{\omega_{25}}$, and the variance of the measurement error σ_{me}^{w}. Standard errors (in parentheses) are based on 500 bootstrap draws of the estimation sample. For both men and women, the wage error process is estimated on the sample of individuals aged 23-61 for whom we observe either reported wages or annual earnings and hours. We do not include wages predicted from only demographics to obtain these estimates. For both men and women, we instrument the lag of the wage error with the second and third lag of the change in the wage error. For men, we also instrument the lags of employment and unemployment with deviations from individual means of these variables. The error component standard deviations are estimated using the method of moments. See Appendix B.2.

Table 2: B.2: Labor Market Status Multinomial Logit Estimates

	Men		Women	
	Unemployed	Employed	Unemployed	Employed
Education	0.04882	0.20166***	0.21362***	0.31706***
	(0.03347)	(0.03182)	(0.03610)	(0.03302)
Married	0.31349***	0.78842***	-0.93472***	-0.12569
	(0.09310)	(0.08790)	(0.18353)	(0.15298)
Children Aged 0-5	-0.07362	-0.09516	-0.76376***	-0.84296***
	(0.08953)	(0.08688)	(0.11160)	(0.10167)
Children Aged 6-12	-0.08768	-0.08544	-0.23526***	-0.36708***
	(0.06382)	(0.06125)	(0.07163)	(0.06633)
Children Aged 13-18	0.05739	0.08513	-0.06239	-0.25201***
	(0.08017)	(0.07425)	(0.08268)	(0.07517)
Married*Children 0-5			-0.12818	0.04329
			(0.12279)	(0.10765)
Married*Children 6-12			0.00163	0.11904*
			(0.08154)	(0.07225)
Married*Children 13-18			0.08659	0.19446**
			(0.09640)	(0.08406)
Potential Experience	0.00445	-0.00452	-0.02445*	-0.01396
	(0.01248)	(0.01177)	(0.01437)	(0.01231)
Potential Experience^2	-0.00379***	-0.00370***	-0.00058	-0.00071
	(0.00098)	(0.00093)	(0.00134)	(0.00119)
Potential Experience^3	0.00002	0.00004	-0.00004	0.00003
	(0.00004)	(0.00004)	(0.00006)	(0.00005)
Married*Education			-0.16889***	-0.16196***
			(0.03448)	(0.03034)
Married*Potential Experience			0.01252	0.02050
			(0.01750)	(0.01495)
Married*Potential Experience^2			-0.00050	-0.00005
			(0.00074)	(0.00058)
Married*Potential Experience^3			-0.00005	-0.00005
			(0.00007)	(0.00006)
Year	-0.10663***	-0.06219***	-0.03894***	-0.01114
	(0.01096)	(0.01057)	(0.01378)	(0.01153)
Year^2	0.00079**	0.00065*	-0.00031	-0.00185***
	(0.00037)	(0.00036)	(0.00088)	(0.00068)
Married*Year^2			-0.00094*	-0.00073*
			(0.00050)	(0.00044)
Cohort*Education	0.01018***	0.00662**	0.00316	0.00628***
	(0.00329)	(0.00315)	(0.00279)	(0.00238)
Cohort^2*Education	0.00022*	0.00018*	0.00007	0.00015*
	(0.00011)	(0.00011)	(0.00009)	(0.00008)
Cohort^3*Education	-0.00002**	-0.00001	-0.00001	-0.00001

	(0.00001)	(0.00001)	(0.00001)	(0.00000)
Cohort*Children 0-5	0.00180	0.00173		
	(0.00566)	(0.00545)		
Cohort*Children 6-12	-0.00697	-0.00858**		
	(0.00439)	(0.00422)		
Cohort*Children 13-18	-0.00294	-0.00254		
	(0.00618)	(0.00586)		
Year^3	0.00006***	0.00004**	-0.00000	-0.00002
	(0.00002)	(0.00002)	(0.00003)	(0.00002)
Lag Unemployed	0.40633***	-1.85353***	0.56668***	-1.12847***
	(0.10072)	(0.09750)	(0.12990)	(0.12165)
Lag Participation	2.30187***	4.93985***	1.71932***	3.65105***
	(0.11518)	(0.10684)	(0.11834)	(0.10175)
Cohort^2	-0.00062**	-0.00037	0.00039	0.00193***
	(0.00030)	(0.00028)	(0.00085)	(0.00065)
Cohort^3	0.00005***	0.00001	0.00002*	0.00003**
	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Cohort*Married			0.01131	0.01533*
			(0.01053)	(0.00916)
Cohort^2*Married			-0.00052	-0.00086***
			(0.00035)	(0.00031)
Cohort*Potential Experience			-0.00107	0.00224*
			(0.00163)	(0.00118)
Cohort*Potential Experience^2			0.00006*	0.00004*
			(0.00003)	(0.00002)
Cohort*Potential Experience^3			0.00001***	0.00001***
			(0.00000)	(0.00000)
Married*Year^3			0.00007**	0.00007***
			(0.00003)	(0.00003)
Married*Lag Paricipation			0.11540	-0.28740***
			(0.13686)	(0.10983)
Married*Lag Unemployed			0.84223***	0.47299***
			(0.16070)	(0.14881)
Constant	0.35258*	-0.17395	-0.22972	0.29851*
	(0.20871)	(0.20374)	(0.18599)	(0.16765)
σ_ν	1.266		1.274	
Observations	52330		55626	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2 displays the coefficients and (standard errors) for the multinomial logit model of labor market status. It includes the normally distributed unobserved heterogeneity component ν. Not participating in the labor force is the base outcome. An individual is considered as not participating in the labor force in a year if they had zero hours worked that year. They are considered unemployed if they worked positive hours but reported positive hours of unemployment or positive weeks of unemployment. We use Stata's Structural Estimation Modeling (SEM) package for estimation. Because we do not observe initial conditions in most cases, we expect initial conditions bias to lead unconstrained MLE estimates to overstate state dependence and understate the importance of unobserved heterogeneity. The samples are restricted to individuals between ages 25 and 61. For those who are married, we exclude individuals whose spouse is over age 61. See the notes to Table B.1a for the variable normalizations.

Table 3: Table B.3a: Log Hours Model

	Men	Women
Wage	0.0894448***	0.2440531***
	(0.0115956)	(0.0157982)
Married	0.0153399**	0.4867076***
	(0.0076294)	(0.0637782)
Education	0.0101206**	-0.0064413
	(0.0040950)	(0.0090840)
Female*Children 0-5		-0.1516126***
		(0.0228351)
Female*Children 6-12		-0.0984253***
		(0.0149795)
Female*Children 13-18		-0.0254972*
		(0.0135567)
Married*Children 0-5		-0.1080793***
		(0.0230237)
Married*Children 6-12		-0.0327831**
		(0.0154117)
Married*Children 13-18		0.0092181
		(0.0149906)
Cohort*Wage	0.0030874***	0.0018028
	(0.0007561)	(0.0011796)
Potential Experience	0.0075485***	-0.0393000**
	(0.0023116)	(0.0163061)
Potential Experience^2	0.0000004	0.0033153**
	(0.0000755)	(0.0013568)
Potential Experience^3	-0.0000083**	0.0000009
	(0.0000033)	(0.0000059)
Year	-0.0113297***	0.0323841**
	(0.0024316)	(0.0164710)
Year^2	-0.0000324	-0.0033995**
	(0.0000205)	(0.0013446)
Year^3	0.0000009	0.0000051**
	(0.0000011)	(0.0000024)
Unemployed	-0.4743167***	-0.3599064***
	(0.0162714)	(0.0220229)
Cohort*Unemployed	-0.0050165***	-0.0054399***
	(0.0008484)	(0.0009315)
Cohort^2*Unemployed	0.0001543***	0.0000792
	(0.0000527)	(0.0000623)
Cohort^2	0.0000179	0.0033024**
	(0.0000220)	(0.0013477)
Education*Potential Experience	0.0008769***	
	(0.0002292)	
Potential Experience^2*Education	-0.0000664***	

	(0.0000161)	
Log Spouse Predicted Wage $\vert Married$		-0.1933049***
		(0.0192936)
Married*Unemployed Spouse		0.0274430*
		(0.0148075)
Married*Unemployed		0.0419086*
		(0.0244356)
Married*Education		0.0101812
		(0.0080597)
Married*Potential Experience		0.0000957
		(0.0016189)
Married*Potential Experience^2		-0.0001512
		(0.0001371)
Married*Year		0.0079887***
		(0.0012980)
Married*Year^2		-0.0002065**
		(0.0000806)
Cohort*Female*Children 0-5		0.0021106**
		(0.0008475)
Cohort*Female*Children 6-12		0.0024499***
		(0.0007315)
Cohort*Female*Children 13-18		0.0011798*
		(0.0006916)
Cohort*Education		0.0073929***
		(0.0027431)
Cohort^2*Education		0.0000081
		(0.0000142)
Cohort*Potential Experience		0.0066149**
		(0.0026883)
Cohort*Potential Experience^2		0.0000043
		(0.0000062)
Cohort*Potential Experience^3		0.0000004
		(0.0000004)
Potential Experience*Education		0.0069052***
		(0.0026197)
Constant	7.4894170***	6.6796133***
	(0.0373006)	(0.1154273)
R-squared	0.10	0.15
Observations	55833	47844

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3a displays estimates from the regression model for log hours. The dependent variable is log(max(200, annual hours)). Standard errors (in parentheses) are clustered at the individual level. The spouse variables are 0 for single women. For both men and women, the models are estimated on the sample of individuals aged 25-61. We instrument marriage with the deviation of marriage from its mean for each individual. We instrument the wage measure using either the reported wage when available or the predicted wage based on demographics. For women, we instrument the variables measuring children, labor market status and the variables interacted with marriage with the deviations from individual means of the variable. See notes to Table B.1a for the variable normalizations.

Table B.3b: Log Hours Error Process

	Men	Women
ρ^h	0.666***	0.722***
	(0.039)	(0.039)
σ_η	0.148***	0.223***
	(0.007)	(0.018)
σ_{u^h}	0.195***	0.244***
	(0.015)	(0.019)
σ_{ϵ^h}	0.232***	0.349***
	(0.011)	(0.013)
$\sigma_{\omega^h_{25}}$	0.298***	0.386***
	(0.017)	(0.018)
σ_{me^h}	0.122	0.122
Number of Moments	13	13

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3b displays parameter estimates for the hours error process. Bootstrap standard errors based on 500 draws of the estimation sample are in parentheses. The parameter ρ^h is the autocorrelation coefficient for the hours error process and σ_η is the standard deviation of unobserved heterogeneity. We assume that η has a truncated normal distribution. As such, in the simulation, we draw η for each individual from a distribution that is truncated at [-1.64,1.64] standard deviations from the mean, but which has been scaled such that the resulting draws of η have standard deviations equal to the estimates displayed in this table. The parameter σ_{u^h} is the standard deviation of the innovation in the hours error process; σ_{ϵ^h} is the standard deviation of the iid error and σ_{me^h} is the standard deviation of measurement error. The latter is assumed to be equal to 0.122. The parameters are estimated by fitting the hours error process to the autocovariances of the hours residual at lags 0 to 11. We use unweighted nonlinear least squares. See Appendix B.3.

Table B.4a: Unearned Income at Age 25

	Age 25		
	Married	Single Men	Single Women
Male Wage	-0.26226***		
	(0.04623)		
Female Wage	0.05482		
	(0.04232)		
Education*Male	0.04118***		
	(0.01238)		
Education*Female	0.00016		
	(0.01371)		
Male Log Hours	-0.51499***		
	(0.04108)		
Female Log Hours	-0.09115***		
	(0.01958)		
Age*Male	0.01860***		
	(0.00697)		
Age*Female	0.03090***		
	(0.00971)		
Year	-0.01006***	-0.00362	-0.00219
	(0.00327)	(0.00431)	(0.00431)
Year^2	-0.00034***	-0.00052***	-0.00025
	(0.00011)	(0.00015)	(0.00015)
Year^3	0.00002*	0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)
Children Aged 0-5	-0.04270*	-0.04666	
	(0.02466)	(0.06567)	
Children Aged 6-12	-0.01679		
	(0.03162)		
Log Hours		-0.45508***	-0.51310***
		(0.04730)	(0.04047)
Wage		-0.03327	-0.10726*
		(0.05043)	(0.05900)
Education		0.01609	0.05597***
		(0.01365)	(0.01488)
Age		0.02824*	0.03613**
		(0.01469)	(0.01527)
Female*Children 0-5			0.33130***
			(0.04790)
Female*Children 6-12			0.34809***
			(0.05381)
Constant	12.66960***	10.84229***	11.27177***
	(0.38678)	(0.41013)	(0.39114)
σ	1.242	1.172	1.116
R-squared	0.06	0.06	0.20
Observations	8105	3266	3231

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4a shows selected estimates from the model of unearned income at age 25 for married men and women, single men, and single women, respectively. Standard errors (in parentheses) are clustered at the individual level. All equations are estimated using ordinary least squares using the sample of individuals aged 23-27. σ indicates the regression's root mean square error. Estimates for after age 25 are displayed in table B.4b. See notes to Table B.1a for the variable normalizations.

Table B.4b: Unearned Income After Age 25

	After Age 25						
	Single Men	Single Women	Men Marrying	Women Marrying	Ongoing Marriage	Men Divorcing	Women Divorcing
Male Wage					-0.34212***		
					(0.02629)		
Female Wage					0.12069***		
					(0.02457)		
Education*Male					0.06038***		
					(0.00960)		
Education*Female					0.05885***		
					(0.01106)		
Male Log Hours					-0.54011***		
					(0.02143)		
Female Log Hours					-0.16870***		
					(0.01471)		
Log Hours	-0.59944***	-0.58204***	-0.49872***	-0.25608***		-0.68264***	-0.42111***
	(0.03303)	(0.02895)	(0.06935)	(0.05270)		(0.07388)	(0.05446)
Wage	0.06237	-0.09186*	-0.09250	0.23870***		-0.02349	0.09992
	(0.05053)	(0.04837)	(0.07580)	(0.09229)		(0.09627)	(0.09864)
Education	0.07928***	0.08649***	0.03135	0.06765***		0.10234***	0.06540***
	(0.01593)	(0.01541)	(0.02042)	(0.02294)		(0.02473)	(0.02529)
Age	0.02448***	0.04037***	0.05173***	0.03149***		0.03176***	0.00900
	(0.00509)	(0.00442)	(0.00898)	(0.01029)		(0.01079)	(0.00943)
Age^2	-0.00022	-0.00071	0.00024	-0.00254**		0.00025	-0.00249*
	(0.00056)	(0.00054)	(0.00107)	(0.00122)		(0.00139)	(0.00134)
Age^3	0.00003	0.00001	-0.00002	0.00014*		0.00000	0.00018***
	(0.00003)	(0.00002)	(0.00006)	(0.00008)		(0.00007)	(0.00007)
Year	-0.01095**	-0.00026	-0.01065	-0.01692**	-0.01236***	-0.01585*	-0.02799***
	(0.00432)	(0.00397)	(0.00651)	(0.00668)	(0.00213)	(0.00838)	(0.00754)
Year^2	-0.00062***	-0.00025	-0.00060**	-0.00053**	-0.00071***	-0.00075**	-0.00060**
	(0.00017)	(0.00017)	(0.00024)	(0.00026)	(0.00007)	(0.00029)	(0.00026)
Year^3	0.00001	-0.00002**	0.00002	0.00002	0.00002***	0.00002	0.00003*
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00000)	(0.00002)	(0.00002)
Children Aged 0-5	0.16711*		-0.01893		-0.06820***	0.28363***	
	(0.09194)		(0.08418)		(0.01746)	(0.09274)	
Female*Children 0-5		0.23692***		0.17254**			0.34509***
		(0.05548)		(0.08024)			(0.07640)
Female*Children 6-12		0.40663***		0.28777***			0.33895***
		(0.03248)		(0.05928)			(0.06203)
Female*Children 13-18		0.47153***		0.22394***			0.32306***
		(0.03826)		(0.08132)			(0.07821)
Age*Male					0.02655***		
					(0.00417)		
Age^2*Male					-0.00024		
					(0.00033)		
Age^3*Male					0.00002**		
					(0.00001)		
Age*Female					0.00849**		
					(0.00423)		
Age^2*Female					-0.00119***		
					(0.00030)		
Age^3*Female					0.00005***		
					(0.00001)		
Children Aged 6-12					-0.03595**		
					(0.01489)		
Children Aged 13-18					-0.00663	0.11748	
					(0.01802)	(0.09109)	
Constant	11.51196***	11.69793***	11.71875***	8.87290***	13.41474***	12.37555***	10.35790***
	(0.28424)	(0.25871)	(0.57990)	(0.46786)	(0.21083)	(0.62240)	(0.47276)
ρ	0.550	0.634	0.464	0.478	0.620	0.483	0.294
σ	1.385	1.327	1.466	1.520	1.540	1.419	1.358
R-squared	0.15	0.22	0.10	0.10	0.13	0.14	0.18
Observations	8475	10952	1592	1592	63042	976	1093

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4b displays selected estimates from the model of unearned income after age 25. Standard errors (in parentheses) are clustered at the individual level. Columns 1-2 refer to single men and women, columns 3-4 to men and women at transitions into marriage, column 5 is for continuing marriages, and the last 2 columns show the estimates for transitions out of marriage. All equations are estimated using OLS including individuals aged 25 and over. σ indicates the regression's root mean square error. ρ indicates the coefficient on a regression of the residual from these regressions on the lag of the residual. This regression is only estimated for years before 1997, as unearned income is observed only biennially after 1996.

Table B.5: Single to Married Transitions Probit Model

	Single to Married
Female	0.03747
	(0.18087)
Education	-0.02424***
	(0.00885)
Education*Female	0.02372*
	(0.01239)
Lag Wage	0.11146***
	(0.02864)
Lag Log Predicted Earnings*Female	-0.09131**
	(0.04195)
Lag Participation	0.26271***
	(0.07120)
Lag Participation*Female	-0.27258***
	(0.08913)
Lag Unemployed	-0.08940**
	(0.04426)
Lag Unemployed*Female	0.14143**
	(0.06168)
Lag Index for Young Children	0.39263***
	(0.06222)
Cohort*Education	0.00111*
	(0.00057)
Cohort*Education*Female	-0.00015
	(0.00075)
Lag Age	-0.01567
	(0.01028)
Lag Age^2	-0.00018
	(0.00019)
Lag Age*Female	0.00367
	(0.00337)
Lag Age^2*Female	-0.00032
	(0.00026)
Year	-0.01729*
	(0.01015)
Year^2	-0.00025***
	(0.00008)
Year^3	0.00001***
	(0.00000)
Cohort*Female	0.01354
	(0.01066)
Cohort^2	-0.00006
	(0.00007)
Cohort*Lag Index for Young Children	-0.01822***
	(0.00521)
Cohort^2*Lag Index for Young Children	0.00064***
	(0.00024)
Constant	-1.32523***
	(0.18112)
Observations	32901

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5 displays MLE probit coefficients for the model of single to married transitions. Standard errors (in parentheses) are clustered at the individual level. The dependent variable is Mar_{it}. We estimate the model for men and women combined using all individuals between age 25 and 61 who were single in $t-1$. The index indicating presence of young children is a variable which increases with 1 for every child younger than 1 year old and increases with 0.5 for every child aged 2-5. See the notes to Table B.1a for the variable normalizations.

Table 4: Table B.6: Probability of Remaining Married Probit Estimates

	Married to Married
Lag Index for Young Children	0.39568***
	(0.03961)
Lag Education*Male	0.04583***
	(0.01107)
Lag Education*Female	0.05601***
	(0.01252)
Female	-0.14991***
	(0.03014)
Absolute Difference Male - Female Education	-0.03127***
	(0.01016)
Absolute Difference Male - Female Age	-0.01838***
	(0.00436)
Lag Age*Male	0.00520
	(0.00452)
Lag Age*Female	0.01204**
	(0.00514)
Lag Age^2*Male	0.00018
	(0.00036)
Lag Age^2*Female	-0.00028
	(0.00035)
Lag Age^3*Male	-0.00001
	(0.00001)
Lag Age^3*Female	0.00001
	(0.00002)
Year	0.00935
	(0.01770)
Year^2	-0.00210*
	(0.00118)
Year^3	-0.00002***
	(0.00001)
Lag Predicted Log Wages*Married*Male	0.13764***
	(0.03235)
Lag Predicted Log Wages*Married*Female	-0.00409
	(0.03391)
Second Lag Participation*Male	0.37711***
	(0.05257)
Second Lag Participation*Female	-0.02441
	(0.03028)
Second Lag Unemployed*Male	-0.09502***
	(0.03663)
Second Lag Unemployed*Female	-0.10672***
	(0.04086)
Absolute Difference Male - Female Married*Earnings	0.06306*

	(0.03812)
Lag Marriage Duration	0.13459*
	(0.06970)
Lag Marriage Duration^2	-0.00186
	(0.00117)
Lag Marriage Duration$^{1/2}$	-0.55256**
	(0.27845)
Cohort^2	0.00020*
	(0.00011)
Cohort*Lag Education*Male	0.00154***
	(0.00054)
Cohort*Lag Education*Female	0.00187***
	(0.00062)
Cohort^2*Lag Education*Male	-0.00002
	(0.00004)
Cohort^2*Lag Education*Female	-0.00010**
	(0.00004)
Cohort Difference Male - Female Education	-0.00060
	(0.00071)
Cohort*Second Lag Participation*Male	0.00733**
	(0.00350)
Cohort*Second Lag Participation*Female	0.00003
	(0.00217)
Cohort*Lag Marriage Duration	0.00249
	(0.00196)
Cohort*Lag Marriage Duration^2	-0.00005
	(0.00004)
Cohort*Lag Marriage Duration$^{1/2}$	-0.00892
	(0.00644)
Year*Lag Marriage Duration	0.00008
	(0.00388)
Year*Lag Marriage Duration^2	-0.00000
	(0.00006)
Year*Lag Marriage Duration$^{1/2}$	-0.00275
	(0.01605)
Year^2*Lag Marriage Duration	-0.00032
	(0.00025)
Year^2*Lag Marriage Duration^2	0.00000
	(0.00000)
Year^2*Lag Marriage Duration$^{1/2}$	0.00174
	(0.00106)
Constant	1.67613***
	(0.32472)
σ_ξ	0.505
Observations	78284

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6 displays MLE probit coefficients for the married to married model. Standard errors are in parentheses. The dependent variable is Mar_{it}. The model includes a normally distributed marriage-specific random effect $\xi_{j(i,t)}$ that captures unobserved heterogeneity in marriage stability. Because surveys occur every other year, we do not know the wages and employment status of spouses in the year preceding the divorce. As a result, we use the second lag of the employment variables in the regression. We also don't use measured wages but instead use predicted wages in the regression. Wages are predicted using, when available, the reported wage, the lag of wage and demographic characteristics. The variables that measure the difference between male and female wages, education and age are computed as absolute differences around the mean arithmetic differences in the sample. The model is estimated using all sample members aged 25-61 who were married in the previous period. See the notes to Table B.1a for the variable normalizations.

Table B.7: Marital Sorting: Model of Spouse's Education

	Male Sample Member		Female Sample Member	
	Age 25	After Age 25	Age 25	After Age 25
Education	0.58634***	0.50846***	0.62332***	0.54441***
	(0.02894)	(0.02799)	(0.03374)	(0.03277)
Children Aged 0-5	-0.36859***		-0.10003**	
	(0.04250)		(0.04406)	
Lag of Children Aged 0-5		-0.24813**		-0.38215***
		(0.11657)		(0.10566)
Lag of Children Aged 6-12		-0.12501*		-0.24349***
		(0.06981)		(0.07133)
Lag of Children Aged 13-18		-0.05475		-0.15983
		(0.11666)		(0.10438)
Age	0.04972***	-0.02110*	0.03875***	-0.00650
	(0.01268)	(0.01090)	(0.01032)	(0.01265)
Age^2		-0.00220*		-0.00076
		(0.00127)		(0.00143)
Age^3		0.00007		0.00004
		(0.00007)		(0.00008)
Year	0.01942***	0.02115***	-0.00676**	0.00136
	(0.00308)	(0.00518)	(0.00326)	(0.00503)
Year^2	0.00002	-0.00034	-0.00009	-0.00032
	(0.00021)	(0.00035)	(0.00025)	(0.00036)
Year*Education	0.00050		-0.00360***	
	(0.00110)		(0.00127)	
Year^2*Education	-0.00002		0.00022**	
	(0.00008)		(0.00010)	
Cohort^2		-0.00020		-0.00029
		(0.00034)		(0.00033)
Cohort*Education		0.00296*		-0.00171
		(0.00178)		(0.00178)
Cohort^2*Education		-0.00001		0.00005
		(0.00010)		(0.00010)
Constant	1.27588***	1.19096***	0.79425***	1.01451***
	(0.13864)	(0.10967)	(0.12464)	(0.13059)
σ_{ED_s}	1.432	1.720	1.706	1.866
R-squared	0.47	0.33	0.38	0.33
Observations	5884	1621	7837	1608

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7 reports selected coefficients from a regression of spouse's years of education on various variables. Standard errors (in parentheses) are clustered at the individual level. Columns 1 and 2 (3 and 4) are spouses of male (female) sample members. The sample for columns 2 and 4 consists of all individuals aged 25-61 who transition from single to married in year t. The sample for columns 1 and 3 consists of observations on marriages that are in progress between age 23 and 27. In the simulations, these estimates are used to generate spouse's education for persons who are married at age 25. The model is estimated using ordinary least squares. See the notes to Table B.1a for the variable normalizations.

Table B.8: Marital Sorting: Model of Spouse's Age

	Male Sample Member		Female Sample Member	
	Age 25	After Age 25	Age 25	After Age 25
Education	0.02436	0.04211	-0.30931***	-0.07716
	(0.03466)	(0.07290)	(0.04708)	(0.08441)
Children Aged 0-5	-0.18675**		0.02856	
	(0.07660)		(0.10263)	
Lag of Children Aged 0-5		-1.23856***		0.03965
		(0.27244)		(0.30229)
Lag of Children Aged 6-12		0.32170		0.38105
		(0.23720)		(0.25127)
Lag of Children Aged 13-18		0.98184***		-0.13222
		(0.33736)		(0.39269)
Age	0.80871***	0.78037***	0.95385***	0.89872***
	(0.02550)	(0.03841)	(0.02471)	(0.04332)
Age^2		0.00103		0.00183
		(0.00357)		(0.00432)
Age^3		0.00011		-0.00001
		(0.00020)		(0.00025)
Year	0.02985***	0.05195***	0.01172**	-0.01281
	(0.00472)	(0.01408)	(0.00563)	(0.01587)
Year^2	-0.00055	0.00006	-0.00101**	-0.00080
	(0.00035)	(0.00103)	(0.00041)	(0.00114)
Cohort^2		-0.00357***		0.00228**
		(0.00099)		(0.00110)
Cohort^2*Age		-0.00030***		0.00012
		(0.00011)		(0.00012)
Constant	-1.97262***	-2.35640***	3.04567***	1.59583***
	(0.26255)	(0.34496)	(0.28219)	(0.38689)
σ_{a_s}	2.780	4.973	3.745	5.716
R-squared	0.17	0.62	0.12	0.59
Observations	5915	1644	7883	1649

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8 displays selected estimates of a regression of spouse's age at the start of the marriage on sample member characteristics, including age. The sample for columns 2 and 4 includes all individuals ages 25-61 in the year that they transition from single to married. These equations are used to simulate spouse's age for marriages that start after age 25. The sample for columns 1 and 3 consists of individuals who are married and between ages 23-27. These equations are used to simulate spouse's age for marriages that are in progress at age 25. The model is estimated using ordinary least squares. Standard errors (in parentheses) are clustered at the individual level. See the notes to Table B.1a for the variable normalizations.

Table B.9: Marital Sorting: Model of Female Spouse's Employment

	Spouse Employment Status	
	Spouse Unemployed	Spouse Employed
Education	0.010173	0.111332***
	(0.047894)	(0.036298)
Lag Wage	0.159804	-0.005910
	(0.155388)	(0.122393)
Potential Experience	-0.029122	-0.011630
	(0.024663)	(0.016765)
Potential Experience^2	-0.001967	-0.001122
	(0.001529)	(0.001206)
Potential Experience^3	-0.000058	0.000067
	(0.000138)	(0.000093)
Lag Children Aged 0-5	-0.491184**	-0.425754***
	(0.201059)	(0.139818)
Lag Children Aged 6-12	-0.010278	-0.056177
	(0.135907)	(0.099732)
Lag Children Aged 13-18	0.248155	-0.076445
	(0.179340)	(0.152891)
Lag Participation	-0.817932	0.438104
	(0.832520)	(0.791148)
Lag Unemployed	-0.422061**	-0.736602***
	(0.215118)	(0.169841)
Year	-0.008859	0.011147*
	(0.006855)	(0.006090)
Year^2	0.000195	-0.000695
	(0.000542)	(0.000443)
Constant	0.120909	1.173552
	(0.977472)	(0.880427)
Observations	1369	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9 displays MLE estimates of a multinomial probit model of spouse's labor force status at the start of marriage for male sample members and female spouses. The coefficients are normed with not participating in the labor force as the reference category. Standard errors (in parentheses) are clustered at the individual level. For the purpose of the marital sorting estimation, we only rely on observed wages and wages predicted using reported wage. That is, the estimation of these models do not include instances in which wage is predicted using only demographics. The model is estimated using male sample members who transition into marriage between age 25 and 61. The simulation model also uses equations that describe initial conditions of marital sorting on employment, which are estimated using individuals aged 23-27 (not reported).

Table B.10: Marial Sorting: Model of Male Spouse's Employment

	Spouse Employment Status	
	Spouse Unemployed	Spouse Employed
Education	0.04341	0.12057*
	(0.06839)	(0.06205)
Lag Wage	0.26704	0.35455
	(0.25423)	(0.24406)
Potential Experience	-0.00861	-0.01502
	(0.01799)	(0.01689)
Potential Experience^2	-0.00048	-0.00117
	(0.00161)	(0.00146)
Lag Children Aged 0-5	-0.05741	-0.07383
	(0.21925)	(0.20347)
Lag Children Aged 6-12	0.20442	-0.02519
	(0.16186)	(0.15299)
Lag Children Aged 13-18	0.14634	0.11642
	(0.20507)	(0.18763)
Lag Participation	0.01087	0.37448
	(0.75960)	(0.70536)
Lag Unemployed	0.02857	-0.36779
	(0.25864)	(0.23542)
Year	-0.02401**	0.00115
	(0.01036)	(0.00977)
Year^2	-0.00049	-0.00090
	(0.00075)	(0.00070)
Constant	0.06381	1.10599
	(1.05358)	(0.99761)
Observations	1290	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10 displays MLE estimates of a multinomial probit model of spouse's labor force status at the start of marriage for female sample members and male spouses. The coefficients are normed with not participating in the labor force as the reference category. Standard errors (in parentheses) are clustered at the individual level. For the purpose of the marital sorting estimation, we only rely on observed wages and wages predicted using reported wage. The model is estimated using male sample members who transition into marriage between age 25 and 61. The simulation model also uses equations that describe initial conditions of marital sorting on employment, which are estimated using individuals aged 23-27.

Table B.11: Marital Sorting: Model of Unobserved Wage Components

	Male Sample Member		*Female Sample Member*	
	Born Before 1962	Born After 1962	Born Before 1962	Born After 1962
$\gamma^{\mu^s}, \gamma^{\omega^s}$	0.300***	0.284***	0.385***	0.383***
	(0.008)	(0.009)	(0.008)	(0.014)
Observations	192	240	192	236

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11 displays estimates of the parameters determining the relationship between sample member and spouse's unobserved wage components, as given by the model presented in Section 3.5.4 in the paper. Standard errors are in parentheses. Given the specification of our sorting model, we require that the estimated γ-parameters be such that $\tilde{\mu}_{si}$ and $\tilde{\omega}_{sit_0}$ have positive variance. To assure this, we constrain the γ-parameters by estimating the difference between the leftmost and rightmost terms in the expressions for the variances of $\tilde{\mu}_{si}$ and $\tilde{\omega}_{sit_0}$ (see section 3.5.4). This difference is constrained to be non-negative. We then recover the γ-parameters from these estimates. Standard errors for the γ-parameters are obtained using the delta method. The parameters are estimated by nonlinear least squares which fits moments of the wage residuals of the spouses at different lags. In estimating these parameters, we only include residuals for sample members and spouses in such cases when the wage is either observed or is imputed using reported wage. That is, we do not use wages that have been predicted based on only demographics for this estimation. See Appendix B.4.

Table B.12: Probit Model of the Probability of Having Another Child

	Men		Women	
	Married	Single	Married	Single
Education	0.06230***	-0.06554**	0.09110***	-0.06150***
	(0.00750)	(0.02619)	(0.00833)	(0.02177)
Lag Children Aged 0-5	-0.00160	0.18006**	-0.04278***	0.17911***
	(0.01464)	(0.07798)	(0.01532)	(0.05143)
Lag Children Aged 6-12	-0.24038***	0.04636	-0.25352***	0.07389*
	(0.01620)	(0.05655)	(0.01577)	(0.03780)
Lag Children Aged 13-18	-0.24277***	0.06480	-0.30425***	-0.12721*
	(0.03503)	(0.09841)	(0.03555)	(0.07568)
Lag Age	-0.01512***	-0.04672**	-0.06795***	-0.07382***
	(0.00520)	(0.01818)	(0.00648)	(0.01643)
Lag Age^2	-0.00237***	-0.00343**	-0.00638***	-0.00469***
	(0.00043)	(0.00139)	(0.00069)	(0.00151)
Lag Age^3	0.00009*	0.00002	-0.00017*	0.00000
	(0.00005)	(0.00022)	(0.00010)	(0.00024)
Year	0.00836***	0.00650	0.00631***	0.00707**
	(0.00199)	(0.00511)	(0.00222)	(0.00340)
Year^2	0.00035***	-0.00073*	0.00024**	-0.00001
	(0.00009)	(0.00043)	(0.00011)	(0.00034)
Cohort*Education	0.00022	-0.00259	0.00082*	0.00149
	(0.00037)	(0.00186)	(0.00045)	(0.00145)
Cohort^2*Education	-0.00010***	-0.00003	-0.00019***	-0.00018**
	(0.00003)	(0.00011)	(0.00003)	(0.00008)
Spouse Age	-0.07218***		-0.01745***	
	(0.00373)		(0.00322)	
Spouse Age^2	-0.00345***		-0.00105***	
	(0.00040)		(0.00031)	
Year^3	-0.00001**		-0.00001**	
	(0.00000)		(0.00000)	
Cohort^2	-0.00025**	0.00023	0.00003	-0.00002
	(0.00010)	(0.00038)	(0.00011)	(0.00031)
Constant	-1.29340***	-2.22331***	-1.29931***	-2.17369***
	(0.03012)	(0.08613)	(0.03587)	(0.08119)
Observations	37986	12169	40438	14969

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12 displays selected MLE probit coefficients and standard errors for the probability of having another child. The model is estimated separately by gender and marital status. Only individuals between ages 25 and 50 are included in the estimation. Married individuals whose spouse is younger than 19 or older than 69 are dropped.

Appendix C Model Fit

This section overlaps heavily with the appendix to AGHV. We simulate 500 lives for each member of the PSID sample to evaluate fit. The procedure is described in Section 3.8. As discussed in the main text, our model fits the data reasonably well overall, but the fit is not perfect. We estimate the model of earnings, marriage, and family income equation by equation—not to make the simulated data from the model match the PSID. Our estimation strategy is mandated by the size and complexity of the model. And the complexity is needed to achieve our goal of quantifying the roles of labor market behavior and marriage formation and sorting in determining the earnings and family income of men and women over the lifecycle.

Section C.1 discusses the fit of the means, standard deviations, and age profiles of key variables and examines the fit of the marital sorting equations. Section C.2 considers the dynamic fit.

C.1 Means, Standard Deviations, and Age Profiles of Key Variables

Appendix tables C.1a, C.1b, and C.1c present means and standard deviations of key variables for the PSID data and simulated data, by cohort group and by gender. Appendix figures C.1-C.10 compare the age profiles of the means of the PSID and simulated data. Lines with circles as markers indicate PSID men. Triangle markers indicate PSID women. The shaded areas indicate 90% confidence intervals around the PSID values for men, and the dash-dotted lines indicate the same for PSID values for women. Simulated values are indicated with a solid line for men and a dashed line for women. Note that in these age profiles and summary statistics tables, we set the wage of all of those outside of the labor force to be the minimum.

C.1.1 Labor Market Outcomes

Labor Force Status. Overall, our model fits the mean, standard deviation, and age profile of employment, unemployment, and nonparticipation quite well, for both men and women. (Tables C.1a-C.1c and Figure C.1 and C.2). We slightly and consistently overestimate women's nonparticipation in the early cohort before age 35. As a result, we slightly and consistently underpredict the employment of the same group.

Wages and Hours. For log wages and log hours, the model fits the means and standard deviations as well as the age profiles for both men and women quite well overall. For the early cohort, the model understates the log wages and hours for women at young ages (Table C.1a and Figure C.3) For the later cohort, the model slightly overpredicts the wage for women at ages 35–45, though it fits the overall age profile reasonably well.

Earnings. The model fits the age profile of log earnings for men quite well overall (Figure C4). For women, the model overpredicts earnings for all cohorts. For example, the overall mean of log earnings for women in the early cohort is 9.08 in the simulated data but 8.97 in the PSID (the miss is 0.11 log points). For the other two cohorts, the miss in the overall mean of log earnings for women is 0.14 log points.

It is important to note that part of the miss between simulated and PSID earnings is the result of their different definitions. Simulated log earnings equals the log wage plus log hours. But as we explained in section 2 the log of our PSID earnings measure is sometimes less than the sum of our PSID log wage and log hours measures. This is why simulated earnings overpredicts PSID earnings for women and to a lesser extent for men even when there is no overprediction for hours or wages. The same issue affects comparison of simulated values of spouse earnings to PSID values of spouse earnings. We do not think it will have much effect on the variance decompositions that we focus on.

C.1.2 Marriage and Fertility

Tables C.1a-C.1c and Figure C.5 show that, on the whole, the model fits the overall marriage rates as well as age profiles fairly well for both men and women. For the early cohort, the model underpredicts marriage rates at young ages for both men and women, but it does better at older ages. As a result of the miss at young ages, the overall marriage rate for men in this cohort is 0.86 in the model and 0.88 in the data, and the corresponding means for women are 0.80 and 0.83. For the late cohort, the model overpredicts marriage somewhat for women at older ages, but it fits the overall marriage rate for women quite well (0.71 in the simulated data versus 0.69 in the PSID).. The tables and figure also show that the model somewhat overpredicts marriage duration (which evolves endogenously in the model) throughout.

Tables C.1a-C.1c and Figure C.6 show that the model fits the distribution of children in the PSID fairly closely overall, though it underpredicts fertility at young ages for the early cohort group.

C.1.3 Family income and nonlabor income

Tables C.1a–C.1c and Figure C.7 show that overall, the model fits the mean, standard deviation, and age profile of log family income for both men and women reasonably well. For the early cohort, the model somewhat underpredicts log family income (y) for women and overpredicts y_ae for men, especially at younger ages. For women in this cohort, the overall mean of log family income is 10.98 in the simulated data and 11.03 in the PSID (the fit for this group is very good for y_ae). For men in this cohort group, the overall mean of y_ae is 11.08 in the simulated data and 11.07 in the PSID. The tables also show that the model somewhat overpredicts the level of nonlabor income and understates its standard deviation for all three cohort groups.

C.1.4 Spouse Labor Market Variables and Marital Sorting

We next consider spouse variables, which are determined by marriage, marital sorting, and by the equations of the earnings model, which determine the evolution of the spouse's outcomes after the marriage begins. Tables C.1a-C.1c show that the model fits the means and standard deviations of spouses' age and education quite well, for all cohorts. The same tables, together with Figures C.8-C.10, show that the fit of spouses' labor force status, log wage, log hours, and log earnings (including their age profiles) is broadly similar to the corresponding fit for sample members (though the miss is a little larger for women at young ages in the early cohort).

Tables C.2a-C.2c compare regression relationships among some key variables for spouses in the simulated data and the PSID. We pool the simulated data and the PSID data and estimate regressions that include interactions between a PSID indicator and key variables. The first two columns in each table report a regression of spouses' education on the education of the corresponding sample member for both married male sample members and married female sample members. The tables show that the simulation overestimate link between education of the spouse and the sample member in the early cohort, underestimates the link in the late cohort group, but does very well for the baby boom cohort. The next two columns in each table examine the association between spouse's age and own age at the start of a marriage. We use a linear spline with knots at 31, 39, and 47. As can be seen in the tables, the age profiles match fairly well. The last two columns in the tables report regressions of the spouse's log wage on the sample member's log wage. These match well between simulated and actual data for the earlier cohorts, but less so for the more recent cohorts. For the later cohort group, the estimated coefficient is somewhat understated in the simulated data for men (0.23 versus 0.34 in the PSID data).

C.2 Dynamic Fit of the Model

To evaluate how well the model replicates the dynamics in the data, we run separate bivariate regressions of the simulated and PSID variables log wage, log hours, employment, log earnings, log unearned income, and log family income on their lags (we do this separately for men and women). We use all observations for each lag rather than a balanced panel. For each variable, Tables C.3a-C.3c report (separately for men and women) estimates of r^k, the autoregression coefficient relating the variable to its lag $t-k$, for $k = 1, 3, 6, 8$. The tables report point estimates from both the simulated data and the PSID. For all cohorts, the model somewhat understates the persistence in earnings for both men and women. For example, for the baby boom cohort, the model understates the coefficient r^k for men by about 0.10 at the first lag and 0.17 at the 8th lag, and for women by about 0.15 at the first lag and 0.14 at the 8th lag. The miss in earnings persistence is primarily driven by an underpredicted persistence in hours (and, for men, the persistence in employment). The persistence in wages is much closer between the simulated and the actual data. The degree of the miss in earnings persistence is broadly similar across cohort groups. The model also understates persistence in nonlabor income (for all cohorts), especially at longer lags.

Table C.1a: Comparison of PSID and Simulated Means and Standard Deviations (Birth Cohorts 1934-44)

	Men				Women			
	PSID		Simulated		PSID		Simulated	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Age	40.97	7.99	40.97	7.99	41.11	7.95	41.11	7.95
Education	12.94	2.53	12.94	2.53	12.58	2.14	12.58	2.14
Log Wage	3.07	0.57	3.06	0.64	2.48	0.56	2.46	0.60
Log Hours	7.63	0.52	7.60	0.55	6.62	1.03	6.59	0.99
Employed	0.86	0.35	0.85	0.36	0.67	0.47	0.62	0.48
Unemployed	0.11	0.32	0.12	0.33	0.07	0.26	0.08	0.26
Nonparticipation	0.03	0.16	0.03	0.16	0.25	0.43	0.30	0.46
Employed to Unemployed	0.07	0.25	0.07	0.26	0.05	0.23	0.06	0.24
Unemployed to Employed	0.50	0.50	0.50	0.50	0.55	0.50	0.59	0.49
Log Earnings	10.64	0.93	10.66	0.94	8.97	1.46	9.08	1.41
Level of Earnings	56167.29	48714.46	60568.52	52479.98	18060.78	19945.90	20466.67	27803.46
Married	0.88	0.33	0.86	0.35	0.83	0.38	0.80	0.40
Marriage Duration | Married	14.00	10.02	15.04	10.41	15.09	11.14	15.42	11.32
$Prob(Married_{t+1} \mid Married_t)$	0.98	0.15	0.98	0.15	0.98	0.15	0.98	0.15
$Prob(Single_{t+1} \mid Married_t)$	0.14	0.35	0.13	0.34	0.09	0.28	0.06	0.24
Children Aged 0-5	0.25	0.56	0.23	0.53	0.17	0.47	0.18	0.47
Children Aged 6-12	0.59	0.86	0.52	0.81	0.52	0.84	0.51	0.83
Children Aged 13-18	0.46	0.73	0.49	0.76	0.48	0.75	0.53	0.82
Age of Spouse | Married	37.87	8.43	38.55	8.39	44.03	9.04	42.94	8.90
Education of Spouse | Married	12.60	1.93	12.55	2.07	12.90	2.74	12.94	2.56
Log Wage of Spouse | Married	2.49	0.57	2.41	0.58	3.08	0.62	3.09	0.65
Log Hours of Spouse | Married	6.47	1.03	6.49	0.98	7.62	0.56	7.58	0.60
Spouse Employed | Married	0.65	0.48	0.60	0.49	0.88	0.32	0.86	0.34
Spouse Unemployed | Married	0.05	0.23	0.07	0.26	0.09	0.28	0.10	0.30
Spouse Nonparticipation | Married	0.29	0.46	0.33	0.47	0.03	0.18	0.04	0.19
Log earnings of Spouse | Married	8.74	1.42	8.92	1.38	10.63	1.05	10.67	1.00
Log Family Income	11.07	0.63	11.08	0.72	11.03	0.70	10.98	0.81
Level of Family Income	77187.42	51790.37	82232.85	60401.13	77142.77	58915.46	78274.36	61268.72
Log of Unearned Income	7.61	1.63	7.76	1.35	7.83	1.68	7.90	1.38
Level of Unearned Income	8821.19	21448.42	6838.82	15015.40	10319.67	23355.63	7925.15	16741.76
Log Family Income AE	10.29	0.70	10.33	0.78	10.29	0.73	10.27	0.83
Observations	8890		4445000		9419		4709500	

Note: This table shows the mean and standard deviations of variables in the PSID data and the simulated data, with 500 simulated lives for each PSID observation by gender, for the 1935–1944 cohort (“early”).

Table C.1b: Comparison of PSID and Simulated Means and Standard Deviations (Birth Cohorts 1945-62)

	Men				Women			
	PSID		Simulated		PSID		Simulated	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Age	39.67	8.79	39.67	8.79	39.64	8.87	39.64	8.87
Education	13.76	2.13	13.76	2.13	13.37	2.10	13.37	2.10
Log Wage	3.09	0.63	3.10	0.65	2.65	0.62	2.66	0.63
Log Hours	7.57	0.58	7.55	0.60	6.92	0.96	6.91	0.93
Employed	0.86	0.35	0.86	0.35	0.75	0.43	0.75	0.44
Unemployed	0.10	0.31	0.10	0.30	0.08	0.27	0.07	0.26
Nonparticipation	0.04	0.19	0.04	0.19	0.17	0.38	0.18	0.38
Employed to Unemployed	0.05	0.22	0.06	0.23	0.05	0.22	0.05	0.23
Unemployed to Employed	0.47	0.50	0.54	0.50	0.55	0.50	0.62	0.49
Log Earnings	10.58	1.08	10.66	1.01	9.45	1.44	9.58	1.35
Level of Earnings	60276.23	91861.97	62752.45	55990.13	26602.25	30460.31	29398.43	34769.73
Married	0.77	0.42	0.79	0.40	0.73	0.44	0.74	0.44
Marriage Duration | Married	9.59	9.25	10.82	9.56	9.68	9.72	10.64	10.04
$Prob(Married_{t+1} \mid Married_t)$	0.97	0.17	0.97	0.16	0.97	0.17	0.97	0.17
$Prob(Single_{t+1} \mid Married_t)$	0.12	0.33	0.13	0.34	0.09	0.28	0.08	0.28
Children Aged 0-5	0.27	0.56	0.25	0.56	0.24	0.54	0.23	0.54
Children Aged 6-12	0.43	0.73	0.42	0.72	0.45	0.75	0.44	0.75
Children Aged 13-18	0.29	0.59	0.35	0.65	0.33	0.62	0.38	0.69
Age of Spouse | Married	38.09	9.14	38.48	9.26	41.49	9.47	41.87	9.68
Education of Spouse | Married	13.60	2.00	13.56	1.97	13.58	2.29	13.61	2.29
Log Wage of Spouse | Married	2.64	0.64	2.64	0.63	3.08	0.62	3.14	0.66
Log Hours of Spouse | Married	6.76	1.00	6.83	0.94	7.56	0.63	7.55	0.61
Spouse Employed | Married	0.73	0.45	0.73	0.44	0.87	0.33	0.87	0.34
Spouse Unemployed | Married	0.06	0.24	0.07	0.25	0.09	0.28	0.09	0.29
Spouse Nonparticipation | Married	0.21	0.41	0.20	0.40	0.04	0.20	0.04	0.19
Log earnings of Spouse | Married	9.27	1.48	9.49	1.37	10.61	1.10	10.70	1.02
Log Family Income	11.07	0.75	11.13	0.75	10.97	0.79	11.01	0.84
Level of Family Income	82407.26	64431.84	87706.47	65474.56	76756.06	61325.19	81974.83	65846.02
Log of Unearned Income	7.56	1.57	7.73	1.32	7.70	1.60	7.85	1.35
Level of Unearned Income	8096.22	21449.95	6413.26	14137.10	8895.97	22280.02	7265.47	15522.38
Log Family Income AE	10.39	0.75	10.44	0.76	10.29	0.79	10.32	0.83
Observations	27658		13829000		29574		14787000	

Note: This table shows the mean and standard deviations of variables in the PSID data and the simulated data, with 500 simulated lives for each PSID observation by gender, for the 1945–1962 (''baby boom") cohort.

Table C.1c: Comparison of PSID and Simulated Means and Standard Deviations (Birth Cohorts 1964-74)

	Men				Women			
	PSID		Simulated		PSID		Simulated	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Age	36.97	7.38	36.97	7.38	37.02	7.50	37.02	7.50
Education	13.61	2.05	13.61	2.05	13.91	1.93	13.91	1.93
Log Wage	3.06	0.64	3.07	0.65	2.73	0.65	2.76	0.65
Log Hours	7.56	0.63	7.51	0.67	7.02	0.95	7.01	0.92
Employed	0.88	0.32	0.87	0.33	0.77	0.42	0.77	0.42
Unemployed	0.07	0.26	0.07	0.26	0.06	0.24	0.07	0.25
Nonparticipation	0.04	0.21	0.06	0.23	0.17	0.38	0.16	0.37
Employed to Unemployed	0.04	0.19	0.04	0.20	0.04	0.19	0.05	0.22
Unemployed to Employed	0.54	0.50	0.62	0.49	0.54	0.50	0.64	0.48
Log Earnings	10.56	1.19	10.58	1.11	9.64	1.49	9.78	1.37
Level of Earnings	64219.75	91900.49	61211.61	56591.22	33186.67	39033.24	35187.66	39755.87
Married	0.71	0.45	0.72	0.45	0.69	0.46	0.71	0.45
Marriage Duration | Married	6.88	7.23	7.88	7.82	7.28	7.75	8.13	8.12
$Prob(Married_{t+1} \| Married_t)$	0.97	0.17	0.97	0.16	0.97	0.18	0.97	0.18
$Prob(Single_{t+1} \| Married_t)$	0.11	0.32	0.11	0.31	0.10	0.30	0.10	0.30
Children Aged 0-5	0.32	0.60	0.31	0.60	0.31	0.58	0.31	0.61
Children Aged 6-12	0.47	0.74	0.45	0.74	0.54	0.77	0.52	0.79
Children Aged 13-18	0.24	0.53	0.30	0.62	0.32	0.60	0.38	0.69
Age of Spouse | Married	36.15	7.79	36.70	8.07	39.18	8.14	39.67	8.50
Education of Spouse | Married	14.04	1.95	13.96	1.99	13.75	2.10	13.86	2.10
Log Wage of Spouse | Married	2.76	0.65	2.74	0.66	3.11	0.61	3.17	0.65
Log Hours of Spouse | Married	6.95	0.99	6.95	0.94	7.56	0.62	7.55	0.62
Spouse Employed | Married	0.77	0.42	0.76	0.43	0.91	0.28	0.90	0.30
Spouse Unemployed | Married	0.05	0.21	0.06	0.23	0.05	0.22	0.06	0.23
Spouse Nonparticipation | Married	0.18	0.38	0.18	0.39	0.04	0.19	0.04	0.20
Log earnings of Spouse | Married	9.63	1.48	9.71	1.40	10.67	1.11	10.73	1.05
Log Family Income	11.09	0.83	11.08	0.85	11.00	0.86	11.04	0.90
Level of Family Income	88247.22	74216.61	88177.77	69898.76	81880.90	68190.96	87282.18	71630.42
Log of Unearned Income	7.36	1.51	7.56	1.26	7.49	1.55	7.69	1.29
Level of Unearned Income	6473.46	16766.61	5166.27	11889.72	7389.50	21158.68	5984.58	13294.33
Log Family Income AE	10.45	0.78	10.46	0.81	10.33	0.83	10.37	0.85
Observations	12036		6018000		13173		6586500	

Note: This table shows the mean and standard deviations of variables in the PSID data and the simulated data, with 500 simulated lives for each PSID observation by gender, for the 1964–1974 cohort (“later”).

Table C.2a: Fit of Spouse Characteristics (Birth Cohorts 1935-44)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	1.296***	1.729**	4.000***	0.219	0.091	-0.448**
	(0.471)	(0.694)	(1.366)	(1.754)	(0.176)	(0.197)
Education	0.548***	0.872***				
	(0.001)	(0.002)				
Log Wage					0.224***	0.251***
					(0.002)	(0.003)
Education × PSID Data	-0.094**	-0.142***				
	(0.037)	(0.053)				
Log Wage × PSID					0.004	0.110
					(0.061)	(0.074)
Age spline 25-31			0.890***	1.011***		
			(0.003)	(0.003)		
Age spline 32-39			0.663***	1.011***		
			(0.006)	(0.008)		
Age spline 40-47			0.787***	0.968***		
			(0.008)	(0.010)		
Age spline 48-55			0.752***	0.983***		
			(0.010)	(0.014)		
Age spline 25-31 × PSID Data			-0.173***	0.041		
			(0.059)	(0.083)		
Age spline 32-39 × PSID Data			0.189	-0.313		
			(0.149)	(0.207)		
Age spline 40-47 × PSID Data			0.061	0.063		
			(0.225)	(0.328)		
Age spline 48-55 × PSID Data			0.309	-0.060		
			(0.230)	(0.372)		
Constant	5.472***	2.017***	0.596***	1.976***	1.789***	2.422***
	(0.018)	(0.025)	(0.058)	(0.069)	(0.007)	(0.009)
R-squared	0.45	0.53	0.81	0.82	0.06	0.06
Observations	3834856	3763615	803505	750900	237439	168482

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table displays, for the 1935–1944 ("early") cohort, results of regressions with the spouse's education, age, and wage as the outcome variable, including both simulated and PSID data in the regressions. Standard errors (in parentheses) are clustered at the individual level. The control variables are the sample member's characteristic, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.2b: Fit of Spouse Characteristics (Birth Cohorts 1945-62)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	-0.367	0.138	0.896	0.441	-0.095	-0.083
	(0.306)	(0.360)	(0.777)	(0.792)	(0.074)	(0.069)
Education	0.542***	0.694***				
	(0.001)	(0.001)				
Log Wage					0.230***	0.253***
					(0.001)	(0.001)
Education × PSID Data	0.030	-0.010				
	(0.023)	(0.026)				
Log Wage × PSID					0.064**	-0.006
					(0.025)	(0.025)
Age spline 25-31			0.893***	0.957***		
			(0.002)	(0.002)		
Age spline 32-39			0.825***	0.881***		
			(0.003)	(0.003)		
Age spline 40-47			0.861***	0.903***		
			(0.004)	(0.005)		
Age spline 48-55			0.868***	0.934***		
			(0.006)	(0.008)		
Age spline 25-31 × PSID Data			-0.040	-0.021		
			(0.032)	(0.034)		
Age spline 32-39 × PSID Data			0.130*	0.079		
			(0.067)	(0.075)		
Age spline 40-47 × PSID Data			-0.100	-0.146		
			(0.096)	(0.099)		
Age spline 48-55 × PSID Data			-0.108	0.257*		
			(0.131)	(0.150)		
Constant	6.076***	4.292***	1.486***	3.673***	1.877***	2.355***
	(0.014)	(0.016)	(0.038)	(0.039)	(0.003)	(0.003)
R-squared	0.34	0.40	0.74	0.74	0.05	0.06
Observations	11007034	10918505	2526591	2479314	1364096	1142485

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table displays, for the 1945–1962 (''baby boom") cohort, results of regressions with the spouse's education, age, and wage as the outcome variable, including both simulated and PSID data in the regressions. Standard errors (in parentheses) are clustered at the individual level. The control variables are the sample member's characteristic, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.2c: Fit of Spouse Characteristics (Birth Cohorts 1964-74)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	-0.088	-1.172**	-0.498	-0.270	-0.296***	-0.187*
	(0.433)	(0.539)	(1.466)	(1.352)	(0.103)	(0.100)
Education	0.577***	0.600***				
	(0.002)	(0.002)				
Log Wage					0.228***	0.230***
					(0.002)	(0.002)
Education $\times$ PSID Data	0.012	0.076**				
	(0.031)	(0.038)				
Log Wage $\times$ PSID					0.103***	0.033
					(0.036)	(0.035)
Age spline 25-31			0.863***	0.899***		
			(0.003)	(0.003)		
Age spline 32-39			0.824***	0.869***		
			(0.004)	(0.005)		
Age spline 40-47			0.881***	0.882***		
			(0.007)	(0.008)		
Age spline 48-55			0.938***	0.886***		
			(0.017)	(0.017)		
Age spline 25-31 $\times$ PSID Data			0.018	0.015		
			(0.058)	(0.054)		
Age spline 32-39 $\times$ PSID Data			-0.073	-0.010		
			(0.091)	(0.098)		
Age spline 40-47 $\times$ PSID Data			-0.169	0.009		
			(0.170)	(0.176)		
Age spline 48-55 $\times$ PSID Data			0.349	0.495**		
			(0.292)	(0.250)		
Constant	6.043***	5.457***	2.965***	5.337***	2.004***	2.402***
	(0.021)	(0.024)	(0.066)	(0.066)	(0.005)	(0.004)
R-squared	0.35	0.30	0.64	0.63	0.05	0.05
Observations	4335309	4697892	1182270	1242843	708238	712601

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table displays, for the 1964–1974 ("later") cohort, results of regressions with the spouse's education, age, and wage as the outcome variable, including both simulated and PSID data in the regressions. Standard errors (in parentheses) are clustered at the individual level. The control variables are the sample member's characteristic, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.3a: Dynamic Fit (Birth Cohorts 1935-44)

Panel A: Men

	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.778	0.782	0.768	0.579	0.476	0.483	0.830	0.725	0.683	0.614	0.836	0.708
	(0.007)		(0.008)		(0.009)		(0.007)		(0.008)		(0.007)	
3	0.718	0.714	0.619	0.375	0.317	0.178	0.753	0.601	0.580	0.264	0.759	0.578
	(0.008)		(0.010)		(0.010)		(0.009)		(0.009)		(0.008)	
6	0.669	0.652	0.544	0.254	0.282	0.093	0.735	0.527	0.500	0.098	0.722	0.490
	(0.010)		(0.014)		(0.012)		(0.014)		(0.012)		(0.010)	
8	0.638	0.626	0.554	0.218	0.263	0.078	0.748	0.505	0.453	0.063	0.689	0.458
	(0.012)		(0.017)		(0.013)		(0.016)		(0.014)		(0.013)	

Panel B: Women

	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.712	0.772	0.833	0.725	0.476	0.657	0.894	0.773	0.704	0.629	0.838	0.718
	(0.008)		(0.006)		(0.009)		(0.004)		(0.008)		(0.006)	
3	0.657	0.689	0.685	0.531	0.317	0.418	0.768	0.600	0.570	0.282	0.767	0.572
	(0.008)		(0.008)		(0.010)		(0.007)		(0.009)		(0.008)	
6	0.623	0.621	0.550	0.391	0.282	0.300	0.652	0.467	0.462	0.105	0.721	0.469
	(0.010)		(0.009)		(0.012)		(0.008)		(0.012)		(0.010)	
8	0.595	0.596	0.486	0.337	0.263	0.264	0.589	0.414	0.388	0.065	0.708	0.430
	(0.012)		(0.010)		(0.013)		(0.010)		(0.013)		(0.012)	

Note: This table shows the dynamic fit of the model for the 1935–1944 ("early") cohort. Each row in the table shows the coefficient, or standard error, estimated when regressing each outcome variable on its own k-*th* lag, as indicated in the leftmost column, using the PSID and simulated data, respectively. Simulations are based on 500 copies for each PSID sample member. Simulation error is negligible.

Table C.3b: Dynamic Fit (Birth Cohorts 1945-62)

Panel A: Men

	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.727	0.768	0.732	0.619	0.509	0.499	0.828	0.730	0.605	0.589	0.820	0.694
	(0.004)		(0.004)		(0.006)		(0.004)		(0.007)		(0.004)	
3	0.669	0.694	0.565	0.411	0.342	0.203	0.712	0.582	0.479	0.234	0.734	0.550
	(0.004)		(0.007)		(0.007)		(0.006)		(0.008)		(0.006)	
6	0.625	0.623	0.469	0.284	0.264	0.109	0.647	0.485	0.405	0.082	0.689	0.460
	(0.006)		(0.008)		(0.007)		(0.008)		(0.008)		(0.007)	
8	0.600	0.593	0.437	0.245	0.231	0.087	0.620	0.453	0.361	0.052	0.672	0.421
	(0.007)		(0.008)		(0.007)		(0.008)		(0.008)		(0.008)	

Panel B: Women

	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.705	0.762	0.800	0.666	0.509	0.589	0.875	0.731	0.634	0.607	0.785	0.704
	(0.004)		(0.004)		(0.006)		(0.003)		(0.006)		(0.004)	
3	0.644	0.680	0.628	0.460	0.342	0.337	0.727	0.546	0.497	0.256	0.694	0.536
	(0.004)		(0.004)		(0.007)		(0.004)		(0.008)		(0.006)	
6	0.606	0.615	0.474	0.333	0.264	0.237	0.595	0.425	0.384	0.097	0.656	0.439
	(0.006)		(0.006)		(0.007)		(0.006)		(0.008)		(0.007)	
8	0.574	0.592	0.395	0.289	0.231	0.210	0.521	0.384	0.326	0.059	0.625	0.395
	(0.006)		(0.007)		(0.007)		(0.007)		(0.008)		(0.008)	

Note: This table shows the dynamic fit of the model for the 1945–1962 (''baby boom") cohort. Each row in the table shows the coefficient, or standard error, estimated when regressing each outcome variable on its own k-*th* lag, as indicated in the leftmost column, using the PSID and simulated data, respectively. Simulations are based on 500 copies for each PSID sample member. Simulation error is negligible.

Table C.3c: Dynamic Fit (Birth Cohorts 1964-74)

Panel A: Men

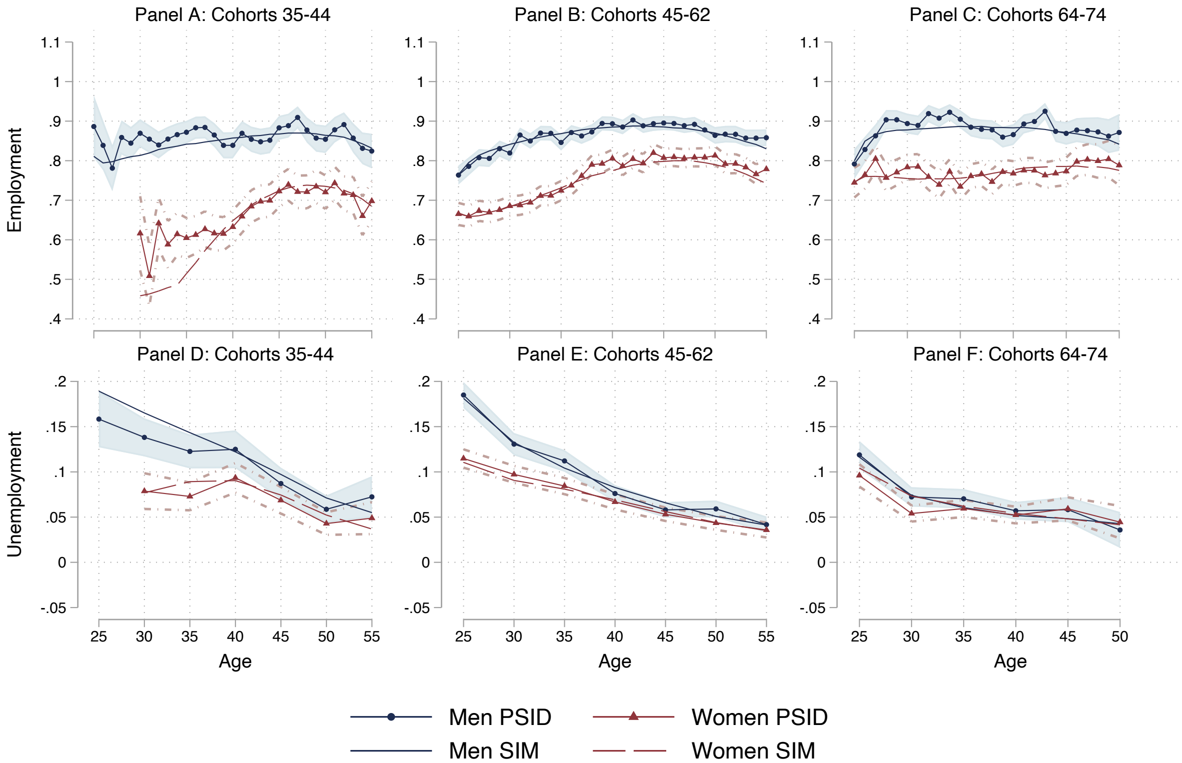
	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.705	0.759	0.762	0.667	0.483	0.542	0.859	0.751	0.379	0.560	0.637	0.652
	(0.007)		(0.007)		(0.008)		(0.006)		(0.029)		(0.024)	
3	0.648	0.680	0.568	0.465	0.303	0.289	0.745	0.597	0.231	0.202	0.540	0.481
	(0.008)		(0.009)		(0.010)		(0.009)		(0.037)		(0.032)	
6	0.647	0.609	0.488	0.342	0.199	0.192	0.709	0.497	0.337	0.074	0.681	0.476
	(0.009)		(0.013)		(0.013)		(0.012)		(0.017)		(0.013)	
8	0.615	0.579	0.441	0.305	0.159	0.163	0.671	0.465	0.314	0.043	0.639	0.439
	(0.010)		(0.016)		(0.014)		(0.014)		(0.017)		(0.016)	

Panel B: Women

	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.702	0.749	0.806	0.656	0.483	0.583	0.888	0.723	0.470	0.586	0.740	0.662
	(0.006)		(0.006)		(0.008)		(0.004)		(0.025)		(0.019)	
3	0.630	0.661	0.643	0.448	0.303	0.337	0.759	0.533	0.356	0.233	0.578	0.458
	(0.007)		(0.008)		(0.010)		(0.008)		(0.032)		(0.028)	
6	0.583	0.592	0.486	0.324	0.199	0.241	0.637	0.418	0.363	0.087	0.644	0.439
	(0.008)		(0.010)		(0.013)		(0.009)		(0.016)		(0.013)	
8	0.563	0.569	0.414	0.287	0.159	0.217	0.565	0.384	0.275	0.052	0.609	0.397
	(0.009)		(0.012)		(0.014)		(0.012)		(0.017)		(0.014)	

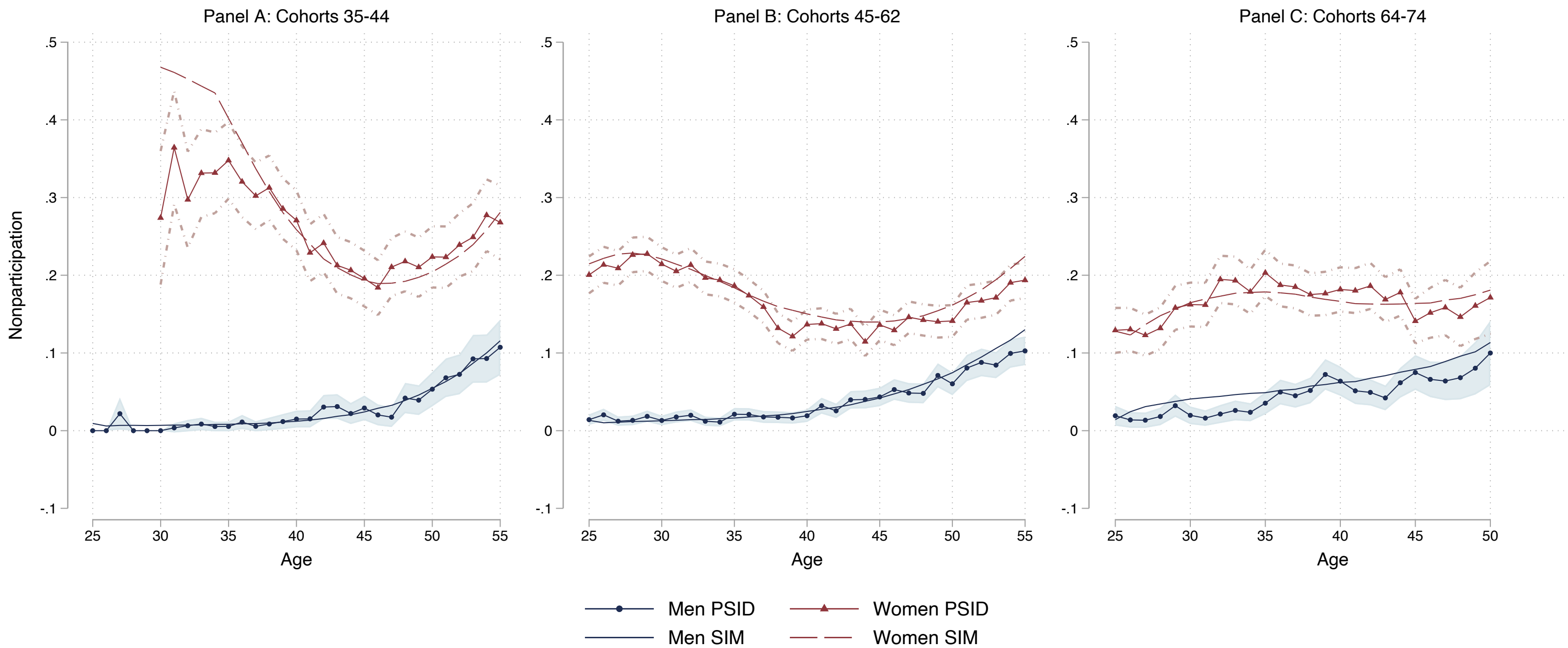
Note: This table shows the dynamic fit of the model for the 1964–1974 ("later") cohort. Each row in the table shows the coefficient, or standard error, estimated when regressing each outcome variable on its own k-*th* lag, as indicated in the leftmost column, using the PSID and simulated data, respectively. Simulations are based on 500 copies for each PSID sample member. Simulation error is negligible.

Figure C.1: Simulated and PSID Age Profiles- Employment and Unemployment



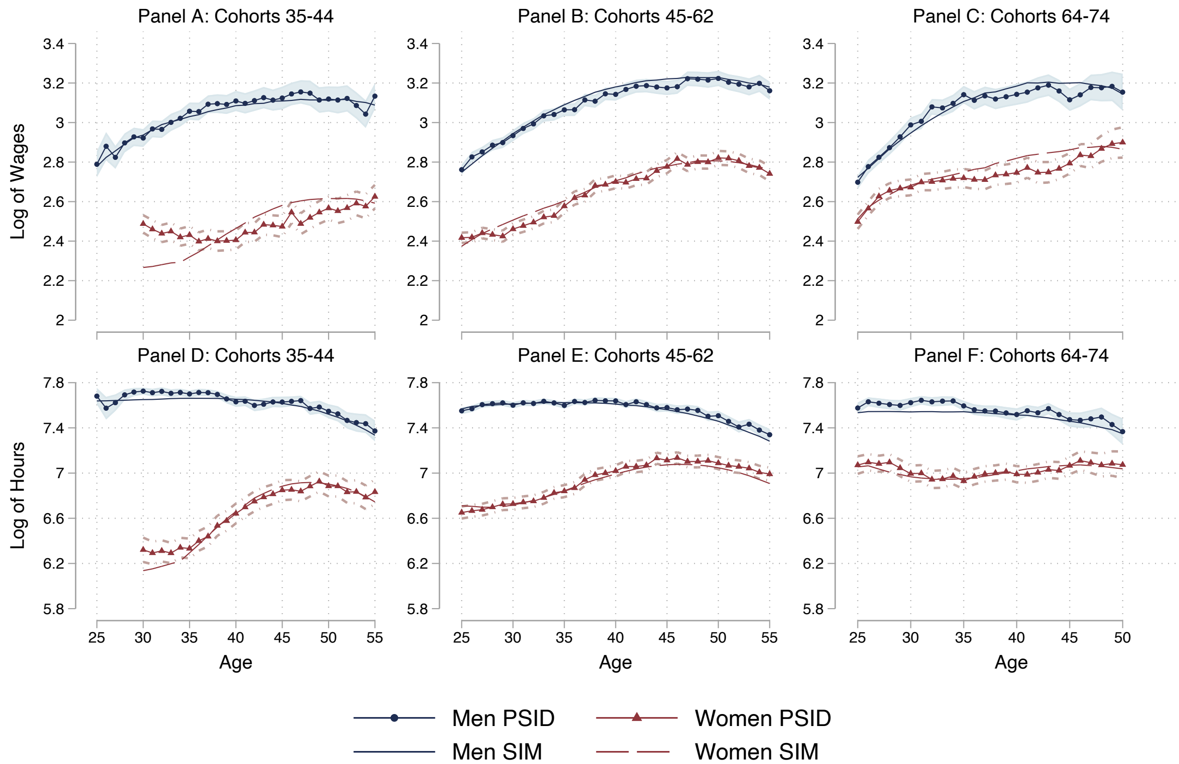
Note: Figures C.1-C.10 display the average values of each key variable at each age for data simulated using the model with estimated parameters and 500 copies per PSID sample member, and the PSID data. The data is graphed separately by cohort group. Because wives' unemployment information is not available in the first five years of the survey, we omit the first age for women from the early cohort (1935–1944) in this and all subsequent fit figures. We also do not report fit at age 55 for the 64-74 cohort because the oldest member of that cohort was only 54 in 2018, the last year of our data. Solid lines with circle and triangle markers refer to male and female PSID sample members, respectively. Solid lines with no markers refer to simulated males and dashed lines to simulated females. The shaded areas indicate 90% confidence bands around the PSID male data points and the dotted lines indicated the same for PSID female sample members. In figure C1, panels A-C display the results for employment and panels D-F for unemployment. To reduce noise in the unemployment panels, the data has been aggregated by five-year intervals.

Figure C.2: Simulated and PSID Age Profiles- Nonparticipation



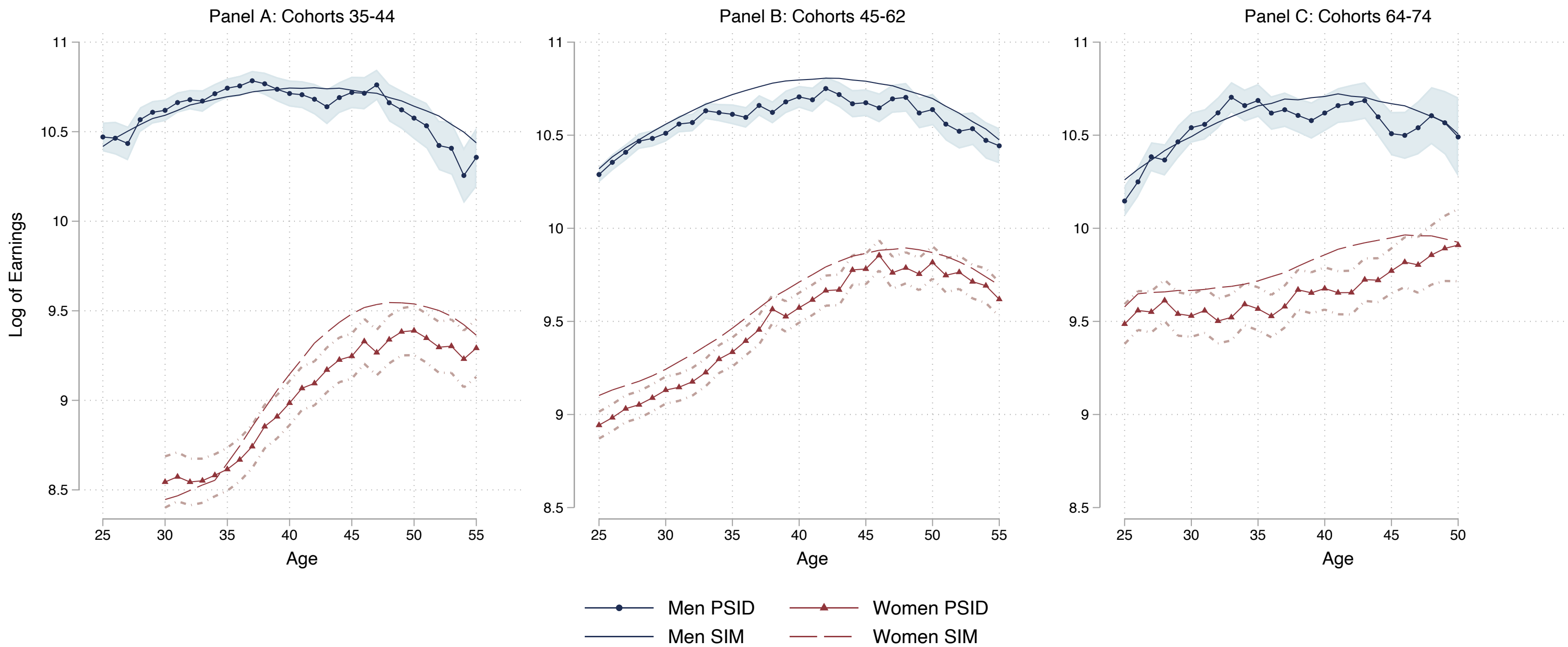
Note: See Figure C.1 notes for further description.

Figure C.3: Simulated and PSID Age Profiles- Wages and Hours



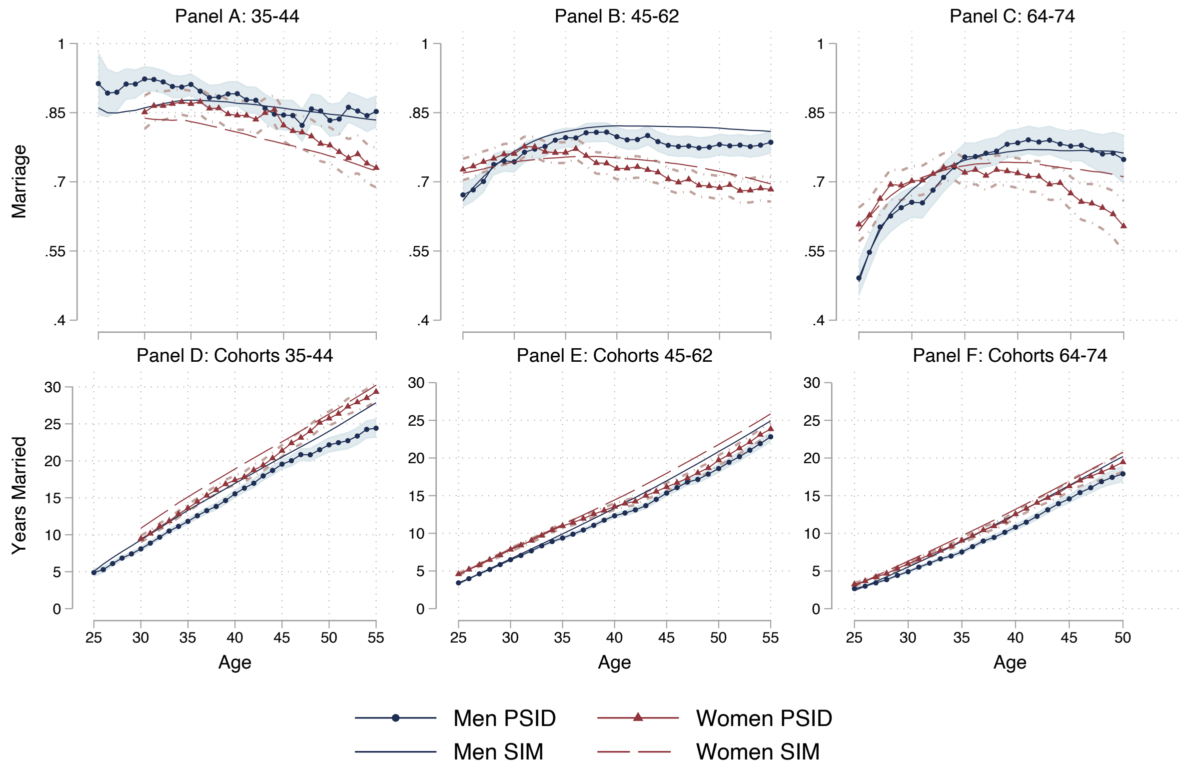
Note: See Figure C.1 notes for further description.

Figure C.4: Simulated and PSID Age Profiles- Earnings



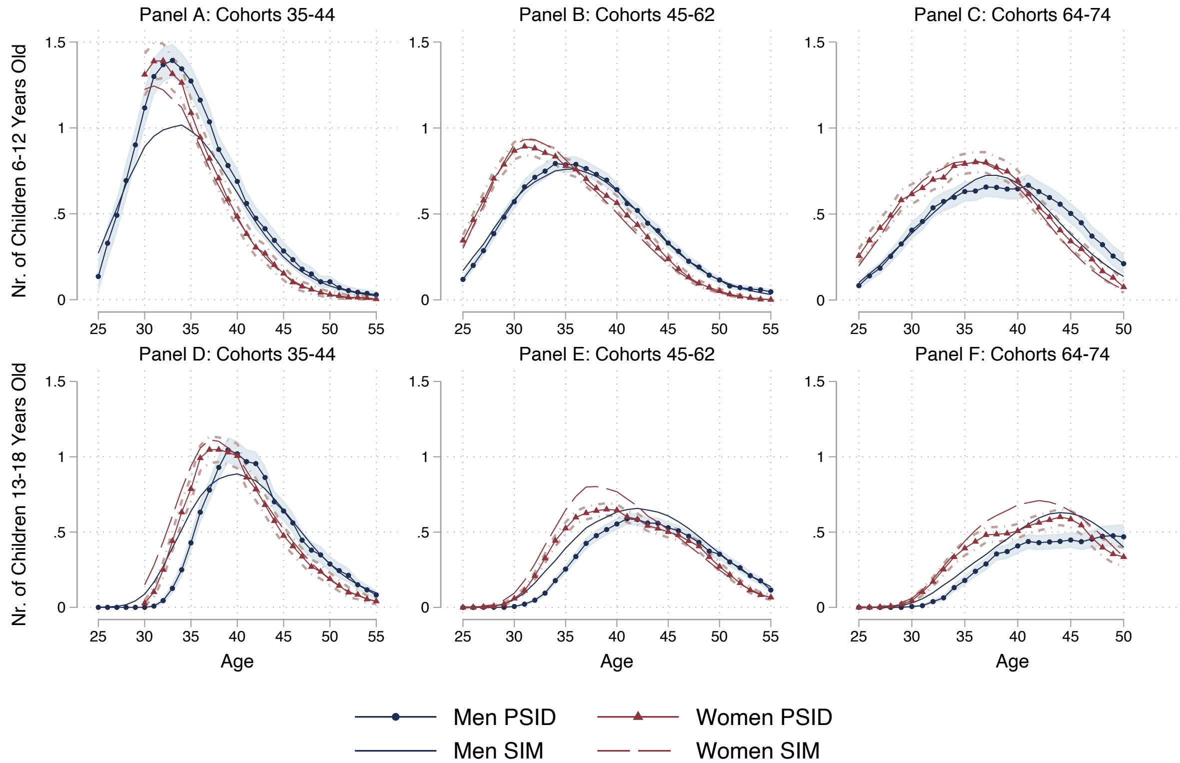
Note: See Figure C.1 notes for further description.

Figure C.5: Simulated and PSID Age Profiles- Marriage and Marriage Duration



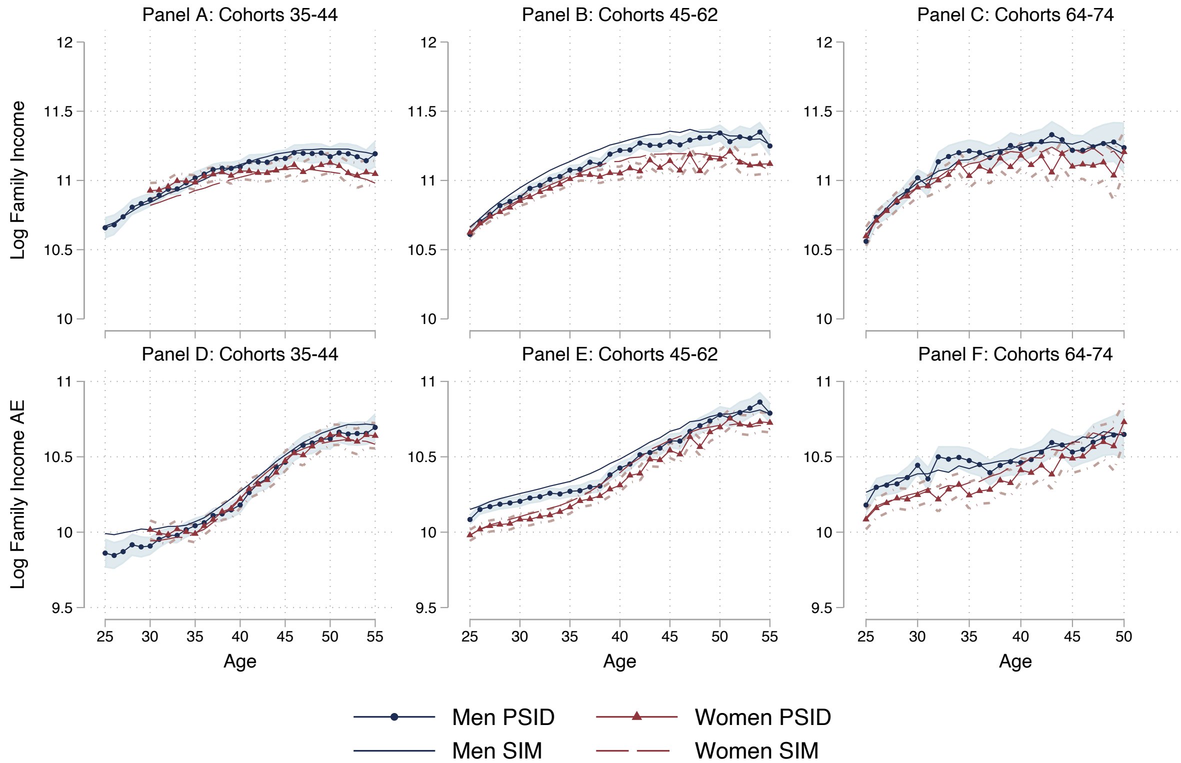
Note: See Figure C.1 notes for further description.

Figure C.6: Simulated and PSID Age Profiles- Children Aged 6-12, 13-18



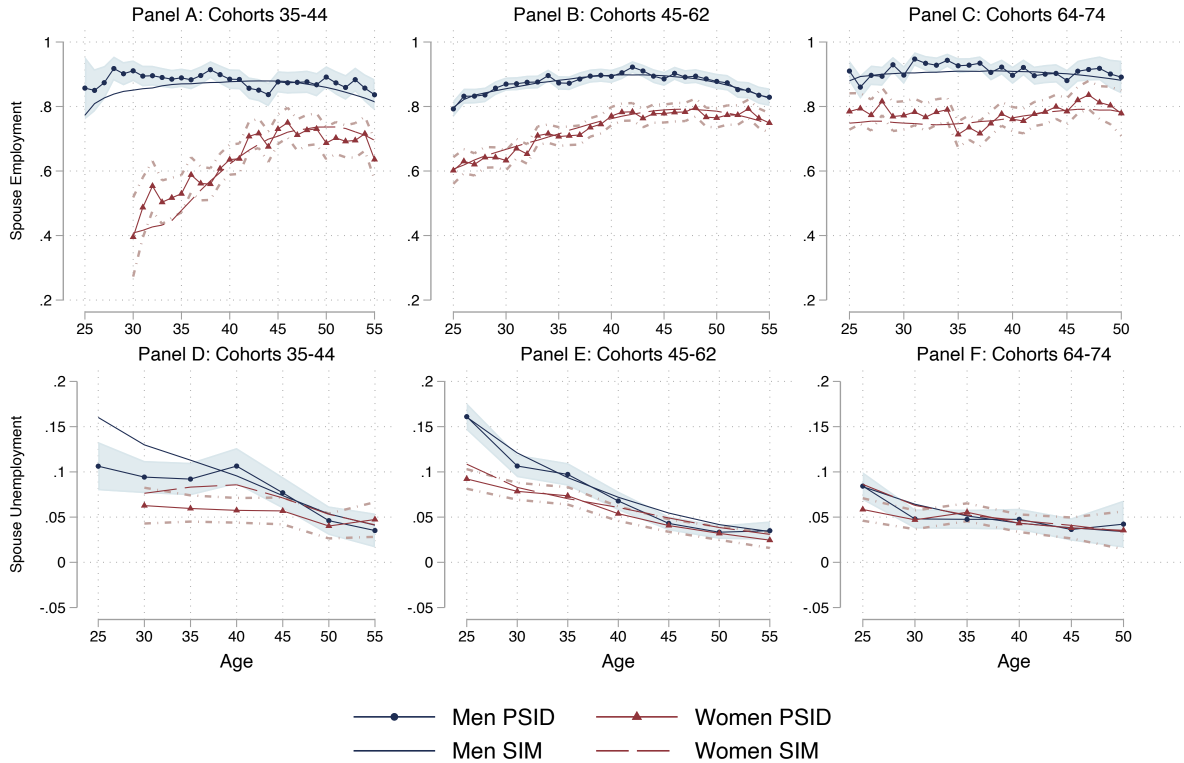
Note: See Figure C.1 notes for further description.

Figure C.7: Simulated and PSID Age Profiles- Family Income and Family Income per Adult Equivalent



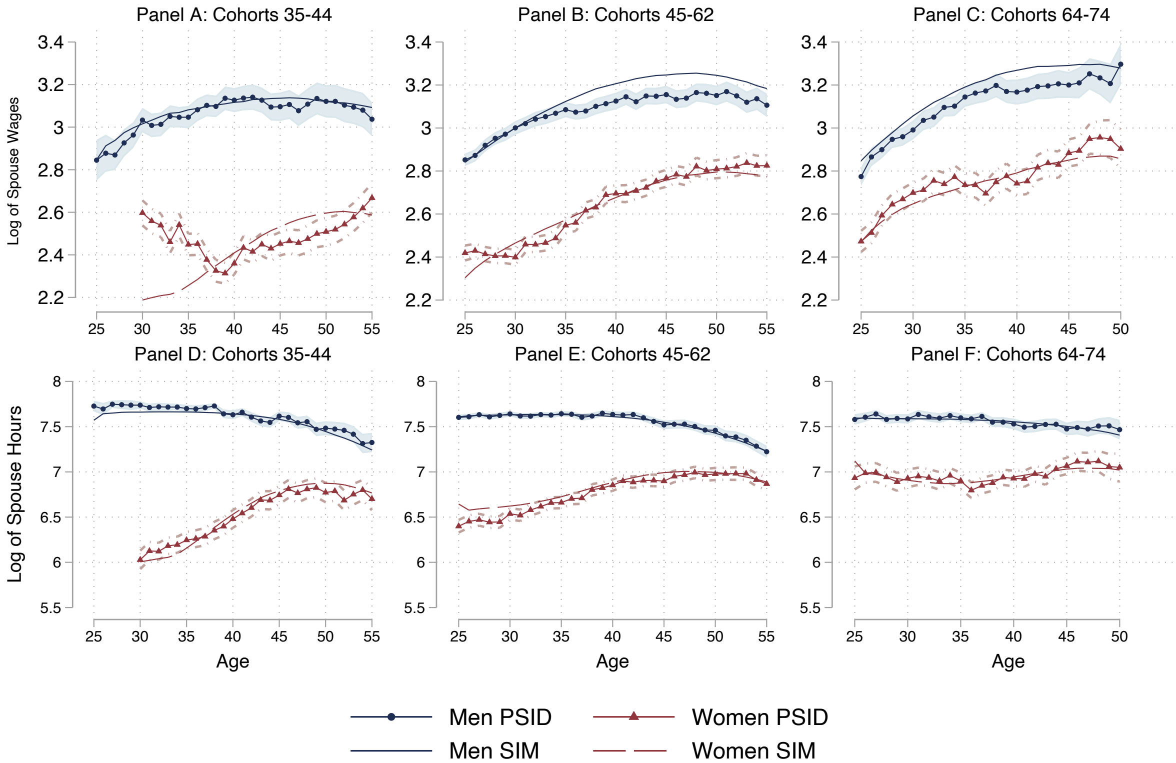
Note: See Figure C.1 notes for further description.

Figure C.8: Simulated and PSID Age Profiles- Spouse Employed and Unemployed



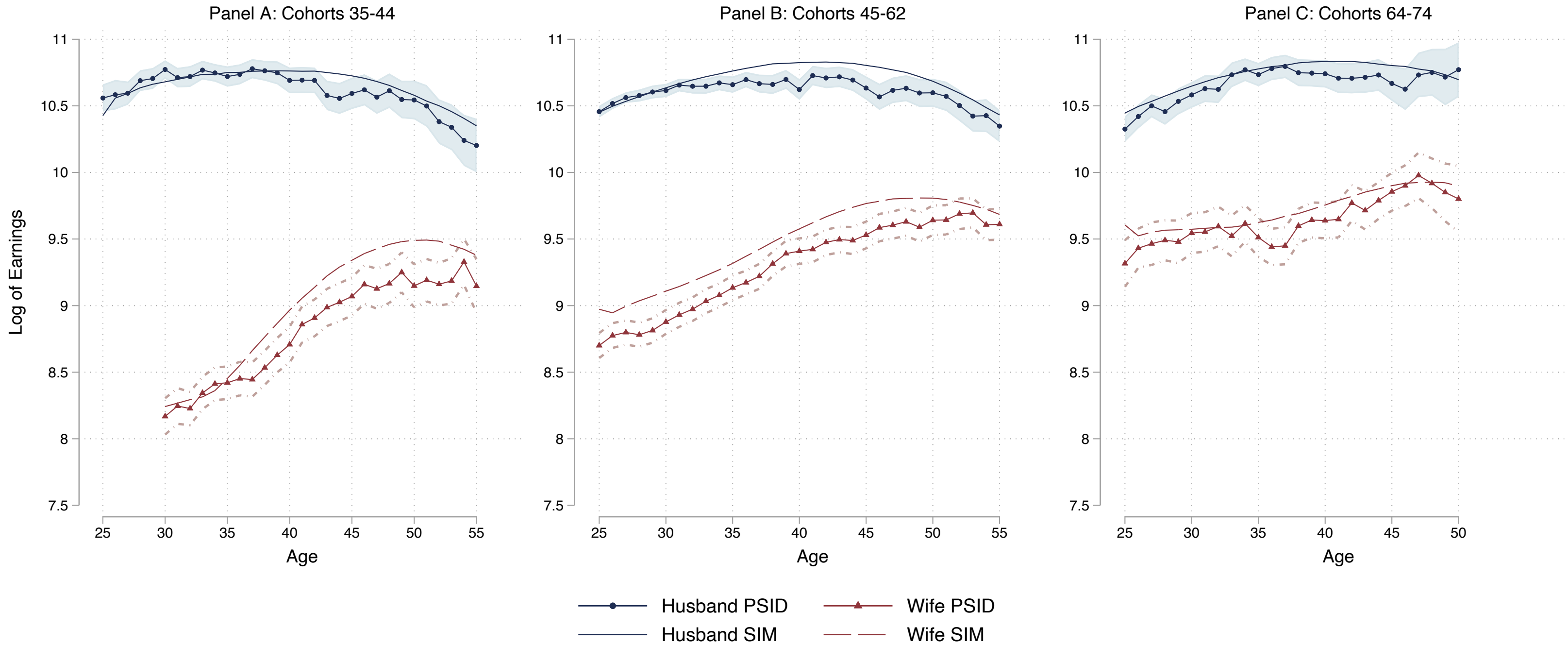
Note: See Figure C.1 notes for further description.

Figure C.9: Simulated and PSID Age Profiles- Spouse Wages and Hours



Note: See Figure C.1 notes for further description.

Figure C.10: Simulated and PSID Age Profiles- Spouse Earnings



Note: See Figure C.1 notes for further description.

Appendix D Additional Regressions Using Simulated Data

Table D.1: Regressions of the Log Wage and Log Hours on Education, Unobserved Variables, and Spouse Variables Using Simulated Data, Age 26–50

		Cohort 35-44						**Cohort 64-74**					
		Male			Female			Male			Female		
Explanatory Variable	Dependant Variable	All (1a)	Single (2a)	Married (3a)	All (4a)	Single (5a)	Married (6a)	All (1b)	Single (2b)	Married (3b)	All (4b)	Single (5b)	Married (6b)
$EDUC$	wage	0.278	0.274	0.279	0.261	0.280	0.250	0.221	0.210	0.222	0.234	0.241	0.230
	hours	*0.053*	*0.087*	*0.051*	*0.160*	*0.166*	*0.149*	*0.119*	*0.156*	*0.091*	*0.116*	*0.205*	*0.106*
μ	wage	0.341	0.335	0.341	0.285	0.307	0.281	0.346	0.342	0.346	0.320	0.318	0.321
	hours	*0.010*	*0.008*	*0.008*	*0.030*	*0.057*	*0.039*	*0.038*	*0.031*	*0.034*	*0.052*	*0.068*	*0.064*
η	wage	-0.0002	0.0002	-0.0004	-0.001	0.001	-0.001	0.0001	0.001	-0.00002	0.0001	0.0004	-0.00000
	hours	*0.138*	*0.139*	*0.137*	*0.143*	*0.195*	*0.130*	*0.132*	*0.127*	*0.134*	*0.177*	*0.181*	*0.175*
ν	wage	0.0004	-0.0001	0.0002	0.046	0.028	0.050	0.001	0.0005	-0.0001	0.042	0.035	0.045
	hours	*0.061*	*0.110*	*0.052*	*0.344*	*0.223*	*0.370*	*0.191*	*0.295*	*0.143*	*0.342*	*0.299*	*0.359*
ω	wage	0.304	0.299	0.303	0.245	0.263	0.241	0.301	0.298	0.301	0.275	0.273	0.275
	hours	*0.017*	*0.016*	*0.015*	*0.035*	*0.046*	*0.033*	*0.036*	*0.033*	*0.034*	*0.054*	*0.058*	*0.055*
ω^h	wage	0.0002	0.0003	0.0002	-0.0003	-0.001	-0.0003	0.0001	-0.00001	0.0001	0.0002	0.0002	0.0001
	hours	*0.243*	*0.241*	*0.243*	*0.222*	*0.296*	*0.205*	*0.234*	*0.223*	*0.238*	*0.279*	*0.285*	*0.277*
Spouse Variables													
$EDUC_s$	wage			0.00003			0.0004			-0.0005			0.004
	hours			*-0.003*			*-0.027*			*-0.003*			*-0.025*
μ_s	wage			0.0003			0.0002			-0.0001			0.0001
	hours			*-0.0001*			*-0.040*			*0.001*			*-0.049*
η_s	wage			0.0002			-0.0005			0.00004			0.0005
	hours			*0.0004*			*0.001*			*-0.0005*			*0.001*
ν_s	wage			-0.00003			0.0005			-0.0001			-0.0003
	hours			*0.001*			*0.001*			*0.001*			*-0.001*
ω_s	wage			0.0001			0.0003			0.00003			-0.0004
	hours			*0.001*			*-0.036*			*0.001*			*-0.047*
ω_s^h	wage			-0.0001			0.0004			-0.00000			0.0001
	hours			*0.0004*			*0.001*			*0.001*			*0.001*

Note: The table reports regressions of log wages or log hours on the explanatory variables listed in the rows using data simulated from the model for age 26 to 50. Rows where hours is the dependent variable are italicized. Columns 1a-6a are for the 1935-44 cohort. Columns 1b-6b are for the 1964-74 cohort. The other column headings indicate gender and marital status. All equations include birth year and a cubic in age. The number of simulated observations is 1,107,500 for column 1a, 957,526 for 2a and 3a, 1,145,000 for 4a, 931,511 for 5a and 6a, 1,862,500 for 1b, 1,347,229 for 2b and 3b, 1,885,000 for 4b, and 1,339,997 for 5b and 6b.

Table D.2: Regressions of Family Income and Earnings on Education, Unobserved Variables, and Spouse Variables Using Simulated Data ,Age 26–30

		Cohort 35-44						**Cohort 64-74**					
		Male			Female			Male			Female		
Explanatory Variable	Dependant Variable	All (1a)	Married (2a)	Married (3a)	All (4a)	Married (5a)	Married (6a)	All (1b)	Married (2b)	Married (3b)	All (4b)	Married (5b)	Married (6b)
$EDUC$	family income	0.258	0.237	0.177	0.277	0.262	0.083	0.208	0.188	0.102	0.242	0.185	0.100
	earnings	*0.214*	*0.216*	*0.217*	*0.379*	*0.297*	*0.293*	*0.189*	*0.182*	*0.179*	*0.338*	*0.320*	*0.314*
μ	family income	0.295	0.294	0.285	0.156	0.131	0.031	0.279	0.247	0.210	0.232	0.192	0.114
	earnings	*0.349*	*0.349*	*0.349*	*0.159*	*0.125*	*0.132*	*0.369*	*0.371*	*0.371*	*0.323*	*0.305*	*0.324*
η	family income	0.114	0.112	0.112	0.042	0.020	0.017	0.093	0.078	0.078	0.090	0.056	0.057
	earnings	*0.138*	*0.137*	*0.137*	*0.098*	*0.076*	*0.077*	*0.138*	*0.140*	*0.140*	*0.182*	*0.176*	*0.176*
ν	family income	0.019	0.018	0.018	0.047	0.039	0.040	0.060	0.032	0.032	0.082	0.066	0.065
	earnings	*0.037*	*0.033*	*0.033*	*0.360*	*0.382*	*0.382*	*0.150*	*0.118*	*0.118*	*0.363*	*0.422*	*0.422*
ω	family income	0.257	0.259	0.258	0.068	0.036	0.024	0.232	0.194	0.188	0.162	0.110	0.099
	earnings	*0.323*	*0.321*	*0.321*	*0.137*	*0.109*	*0.110*	*0.332*	*0.332*	*0.332*	*0.279*	*0.268*	*0.271*
ω^h	family income	0.202	0.200	0.199	0.057	0.025	0.025	0.165	0.140	0.143	0.143	0.091	0.093
	earnings	*0.245*	*0.245*	*0.245*	*0.151*	*0.125*	*0.125*	*0.242*	*0.243*	*0.243*	*0.287*	*0.277*	*0.276*
Spouse Variables													
$EDUC_s$	family income			0.087			0.219			0.139			0.145
	earnings			*-0.002*			*0.006*			*0.004*			*0.011*
μ_s	family income			0.030			0.279			0.126			0.215
	earnings			*-0.00003*			*-0.020*			*0.002*			*-0.052*
η_s	family income			0.016			0.111			0.061			0.084
	earnings			*0.00003*			*0.001*			*-0.003*			*0.003*
ν_s	family income			0.038			0.031			0.059			0.026
	earnings			*0.0004*			*-0.001*			*0.0001*			*-0.003*
ω_s	family income			0.026			0.258			0.106			0.197
	earnings			*-0.0003*			*-0.020*			*-0.001*			*-0.044*
ω_s^h	family income			0.031			0.201			0.104			0.152
	earnings			*-0.001*			*0.00003*			*0.001*			*-0.002*

Note: The table reports regressions of log earnings or log family income per adult equivalent on the explanatory variables listed in the rows using data simulated from the model for age 26 to 30. Rows where earnings is the dependent variable are italicized. Columns 1a-6a are for the 1935-44 cohort. Columns 1b-6b are for the 1964-74 cohort. The other column headings indicate gender and marital status. All equations include birth year and a cubic in age. All explanatory variables are in standard deviation units for the specific gender-cohort-age group. The number of simulated observations is 1,107,500 for column 1a, 957,526 for 2a and 3a, 1,145,000 for 4a, 931,511 for 5a and 6a, 1,862,500 for 1b, 1,347,229 for 2b and 3b, 1,885,000 for 4b, and 1,339,997 for 5b and 6b.

Table D.3: Regressions of Family Income and Earnings on Education, Unobserved Variables, and Spouse Variables Using Simulated Data, Age 46–50

		Cohort 35-44						**Cohort 64-74**					
		Male			Female			Male			Female		
Explanatory Variable	Dependant Variable	All (1a)	Married (2a)	Married (3a)	All (4a)	Married (5a)	Married (6a)	All (1b)	Married (2b)	Married (3b)	All (4b)	Married (5b)	Married (6b)
$EDUC$	family income	0.305	0.290	0.219	0.305	0.299	0.118	0.318	0.242	0.160	0.288	0.192	0.092
	earnings	*0.450*	*0.438*	*0.439*	*0.442*	*0.416*	*0.448*	*0.513*	*0.442*	*0.446*	*0.420*	*0.373*	*0.394*
μ	family income	0.235	0.226	0.196	0.192	0.163	0.097	0.255	0.233	0.196	0.232	0.208	0.139
	earnings	*0.341*	*0.339*	*0.339*	*0.287*	*0.270*	*0.289*	*0.354*	*0.357*	*0.357*	*0.321*	*0.321*	*0.336*
η	family income	0.083	0.078	0.080	0.072	0.050	0.047	0.084	0.078	0.077	0.087	0.067	0.066
	earnings	*0.136*	*0.134*	*0.134*	*0.170*	*0.163*	*0.164*	*0.132*	*0.136*	*0.136*	*0.172*	*0.176*	*0.176*
ν	family income	0.053	0.039	0.040	0.095	0.079	0.079	0.159	0.075	0.076	0.164	0.100	0.101
	earnings	*0.198*	*0.173*	*0.173*	*0.545*	*0.599*	*0.599*	*0.411*	*0.304*	*0.304*	*0.607*	*0.599*	*0.599*
ω	family income	0.189	0.175	0.174	0.120	0.084	0.083	0.195	0.173	0.171	0.154	0.119	0.118
	earnings	*0.304*	*0.302*	*0.302*	*0.260*	*0.253*	*0.253*	*0.306*	*0.313*	*0.313*	*0.288*	*0.290*	*0.291*
ω^h	family income	0.153	0.146	0.146	0.108	0.076	0.076	0.147	0.139	0.138	0.136	0.103	0.104
	earnings	*0.236*	*0.238*	*0.238*	*0.271*	*0.266*	*0.266*	*0.225*	*0.233*	*0.233*	*0.278*	*0.284*	*0.283*
Spouse Variables													
$EDUC_s$	family income			0.106			0.242			0.138			0.185
	earnings			*-0.001*			*-0.041*			*-0.006*			*-0.039*
μ_s	family income			0.099			0.188			0.136			0.195
	earnings			*0.001*			*-0.055*			*0.002*			*-0.042*
η_s	family income			0.049			0.080			0.068			0.075
	earnings			*-0.003*			*0.001*			*0.004*			*0.0004*
ν_s	family income			0.076			0.055			0.099			0.070
	earnings			*0.003*			*0.002*			*0.002*			*0.001*
ω_s	family income			0.086			0.176			0.118			0.168
	earnings			*0.005*			*-0.050*			*0.003*			*-0.048*
ω_s^h	family income			0.083			0.145			0.107			0.149
	earnings			*0.00001*			*-0.001*			*-0.003*			*0.005*

Note: The table reports regressions of log earnings or log family income per adult equivalent on the explanatory variables listed in the rows using data simulated from the model for age 46 to 50. Rows where earnings is the dependent variable are italicized. Columns 1a-6a are for the 1935-44 cohort. Columns 1b-6b are for the 1964-74 cohort. The other column headings indicate gender and marital status. All equations include birth year and a cubic in age. All explanatory variables are in standard deviation units for the specific gender-cohort-age group. The number of simulated observations is 1,107,500 for column 1a, 957,526 for 2a and 3a, 1,145,000 for 4a, 931,511 for 5a and 6a, 1,862,500 for 1b, 1,347,229 for 2b and 3b, 1,885,000 for 4b, and 1,339,997 for 5b and 6b.

Appendix E Additional Variance Decomposition Tables and Figures

Table E.1a: Contributions to Variance of Outcomes at Various Ages - Men Born 1935–1944

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.028	0.124	0.023	0.046	0.071	0.058	0.113	0.000	0.006	-0.003	0.001	0.012	0.002	10.528	0.455	105.769
	(0.024)	(0.012)	(0.007)	(0.022)	(0.033)	(0.009)	(0.009)	(0.000)	(0.007)	(0.007)	(0.007)	(0.007)	(0.002)	(0.034)	(0.054)	(11.722)
age = 30	0.069	0.101	0.017	0.057	0.087	0.091	0.095	0.000	0.002	-0.008	-0.013	-0.009	0.002	10.614	0.537	91.386
	(0.025)	(0.011)	(0.008)	(0.037)	(0.032)	(0.010)	(0.009)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)	(0.029)	(0.057)	(11.051)
age = 35	0.132	0.119	0.024	0.068	0.097	0.107	0.100	0.000	0.008	0.003	-0.000	0.005	0.005	10.678	0.605	110.426
	(0.028)	(0.012)	(0.009)	(0.029)	(0.019)	(0.011)	(0.009)	(0.000)	(0.009)	(0.008)	(0.009)	(0.009)	(0.001)	(0.027)	(0.045)	(10.865)
age = 40	0.168	0.105	0.005	0.096	0.126	0.092	0.091	0.000	-0.000	-0.010	-0.005	-0.010	0.011	10.714	0.681	98.147
	(0.037)	(0.014)	(0.011)	(0.031)	(0.021)	(0.012)	(0.011)	(0.000)	(0.010)	(0.010)	(0.011)	(0.010)	(0.002)	(0.030)	(0.052)	(11.376)
age = 45	0.230	0.137	0.035	0.218	0.228	0.110	0.097	0.000	0.002	0.009	0.004	0.012	0.013	10.693	0.866	126.560
	(0.057)	(0.015)	(0.013)	(0.043)	(0.029)	(0.014)	(0.013)	(0.000)	(0.014)	(0.013)	(0.013)	(0.013)	(0.005)	(0.036)	(0.081)	(10.665)
age = 50	0.303	0.108	0.027	0.401	0.400	0.096	0.075	0.000	-0.005	-0.013	0.004	-0.022	0.030	10.586	1.238	113.560
	(0.085)	(0.020)	(0.020)	(0.056)	(0.045)	(0.018)	(0.018)	(0.000)	(0.017)	(0.018)	(0.017)	(0.018)	(0.009)	(0.049)	(0.132)	(11.117)
Log Family Income																
c1*age = 26*	0.032	0.099	0.016	0.018	0.022	0.043	0.080	-0.012	0.002	0.005	0.002	0.011	0.008	10.695	0.351	92.674
	(0.011)	(0.008)	(0.004)	(0.009)	(0.008)	(0.006)	(0.006)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.030)	(0.022)	(8.575)
age = 30	0.056	0.082	0.011	0.014	0.024	0.061	0.064	-0.010	-0.001	-0.001	-0.006	-0.002	0.010	10.830	0.402	75.340
	(0.012)	(0.008)	(0.004)	(0.013)	(0.008)	(0.006)	(0.005)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.025)	(0.022)	(8.400)
age = 35	0.097	0.082	0.013	0.017	0.023	0.070	0.061	-0.005	0.008	0.011	0.002	0.009	0.017	10.965	0.434	93.602
	(0.013)	(0.007)	(0.005)	(0.009)	(0.006)	(0.006)	(0.005)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.023)	(0.019)	(8.261)
age = 40	0.110	0.068	-0.002	0.014	0.015	0.051	0.050	-0.006	0.003	0.005	0.004	0.001	0.026	11.090	0.444	76.375
	(0.014)	(0.007)	(0.005)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.024)	(0.020)	(8.243)
age = 45	0.126	0.082	0.014	0.046	0.021	0.054	0.052	0.003	0.014	0.015	0.014	0.013	0.042	11.167	0.479	103.211
	(0.018)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.026)	(0.025)	(9.216)
age = 50	0.134	0.064	0.007	0.069	0.013	0.052	0.045	0.028	0.008	0.019	0.016	0.007	0.061	11.186	0.541	96.430
	(0.025)	(0.009)	(0.007)	(0.013)	(0.013)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.028)	(0.035)	(10.199)
Log Family Income AE																
c1*age = 26*	0.054	0.095	0.018	0.018	0.026	0.042	0.083	-0.011	0.004	0.008	0.004	0.014	0.066	9.982	0.471	89.418
	(0.011)	(0.008)	(0.005)	(0.009)	(0.009)	(0.006)	(0.006)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.033)	(0.023)	(7.534)
age = 30	0.086	0.079	0.018	0.016	0.027	0.065	0.071	-0.011	0.002	0.002	-0.003	0.004	0.057	9.996	0.525	78.536
	(0.014)	(0.008)	(0.005)	(0.013)	(0.009)	(0.006)	(0.005)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.032)	(0.024)	(7.417)
age = 35	0.118	0.076	0.017	0.017	0.027	0.070	0.061	-0.007	0.007	0.014	0.001	0.010	0.037	10.057	0.530	84.085
	(0.016)	(0.007)	(0.005)	(0.009)	(0.007)	(0.006)	(0.005)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.031)	(0.022)	(7.577)
age = 40	0.111	0.058	-0.003	0.009	0.017	0.050	0.049	-0.006	0.003	0.003	0.001	-0.000	0.015	10.249	0.499	61.661
	(0.017)	(0.007)	(0.005)	(0.008)	(0.007)	(0.007)	(0.006)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.030)	(0.022)	(8.134)
age = 45	0.113	0.072	0.014	0.041	0.025	0.050	0.051	0.005	0.010	0.012	0.015	0.009	0.012	10.484	0.490	87.369
	(0.018)	(0.007)	(0.005)	(0.009)	(0.008)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.002)	(0.028)	(0.023)	(8.610)
age = 50	0.120	0.057	0.005	0.059	0.017	0.049	0.044	0.030	0.003	0.018	0.020	0.005	0.016	10.640	0.510	86.966
	(0.021)	(0.008)	(0.006)	(0.011)	(0.011)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.004)	(0.025)	(0.029)	(9.661)

Table E.1b: Contributions to Variance of Outcomes at Various Ages - Men Born 1935–1944 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.029	0.114	0.000	0.001	-0.002	0.053	-0.001	0.000	-0.001	-0.002	0.001	-0.001	0.001	2.884	0.214	89.820
	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.025)	(0.006)	(6.584)
age = 30	0.054	0.107	0.002	-0.002	0.002	0.088	-0.001	0.000	-0.001	-0.004	-0.003	-0.003	0.001	2.958	0.287	83.154
	(0.006)	(0.008)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)	(0.000)	(0.003)	(0.003)	(0.002)	(0.003)	(0.000)	(0.020)	(0.008)	(6.699)
age = 35	0.090	0.109	0.002	0.004	0.009	0.098	0.000	0.000	0.002	0.001	0.004	0.003	0.001	3.022	0.332	97.362
	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.020)	(0.010)	(6.008)
age = 40	0.109	0.109	-0.000	0.001	0.008	0.098	-0.001	0.000	0.001	-0.003	0.000	0.000	0.001	3.072	0.352	91.422
	(0.010)	(0.008)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.022)	(0.012)	(6.424)
age = 45	0.116	0.109	0.002	0.003	0.007	0.099	-0.003	0.000	-0.003	0.001	0.002	-0.003	0.001	3.105	0.358	92.391
	(0.011)	(0.008)	(0.003)	(0.003)	(0.004)	(0.007)	(0.003)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.023)	(0.012)	(6.355)
age = 50	0.110	0.114	0.001	0.002	0.010	0.104	0.001	0.000	-0.000	-0.001	0.003	0.000	0.001	3.135	0.350	98.770
	(0.012)	(0.008)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.024)	(0.013)	(6.444)
Log Hours																
c1*age = 26*	0.002	0.003	0.020	0.025	0.045	0.001	0.115	0.000	0.004	-0.001	-0.000	0.005	0.000	7.651	0.190	115.205
	(0.011)	(0.003)	(0.004)	(0.011)	(0.021)	(0.004)	(0.006)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.023)	(0.026)	(13.270)
age = 30	0.007	-0.002	0.017	0.029	0.050	0.000	0.104	0.000	0.003	-0.001	-0.005	-0.001	0.000	7.662	0.185	108.492
	(0.011)	(0.004)	(0.004)	(0.018)	(0.019)	(0.003)	(0.005)	(0.000)	(0.003)	(0.004)	(0.004)	(0.004)	(0.000)	(0.019)	(0.026)	(14.968)
age = 35	0.013	0.004	0.020	0.032	0.051	0.004	0.104	0.000	0.002	0.001	-0.002	0.002	0.001	7.663	0.187	122.731
	(0.011)	(0.004)	(0.004)	(0.013)	(0.012)	(0.004)	(0.005)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.014)	(0.020)	(14.395)
age = 40	0.020	-0.002	0.013	0.045	0.070	-0.003	0.101	0.000	-0.001	-0.002	-0.000	-0.006	0.004	7.653	0.209	114.247
	(0.015)	(0.004)	(0.005)	(0.014)	(0.013)	(0.004)	(0.006)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.014)	(0.022)	(15.467)
age = 45	0.044	0.009	0.022	0.094	0.127	0.006	0.104	0.000	0.001	0.004	0.002	0.004	0.005	7.613	0.286	147.261
	(0.024)	(0.006)	(0.006)	(0.019)	(0.018)	(0.005)	(0.006)	(0.000)	(0.006)	(0.006)	(0.006)	(0.005)	(0.002)	(0.020)	(0.035)	(13.606)
age = 50	0.078	-0.000	0.021	0.171	0.220	-0.000	0.093	0.000	0.000	-0.003	0.003	-0.008	0.014	7.510	0.449	131.420
	(0.034)	(0.008)	(0.008)	(0.024)	(0.023)	(0.007)	(0.008)	(0.000)	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)	(0.030)	(0.056)	(12.561)
Log Family Earnings																
c1*age = 26*	0.032	0.109	0.023	0.033	0.046	0.050	0.096	0.000	0.004	0.002	0.002	0.016	0.009	10.634	0.406	103.834
	(0.020)	(0.010)	(0.006)	(0.015)	(0.019)	(0.008)	(0.008)	(0.000)	(0.005)	(0.006)	(0.005)	(0.006)	(0.003)	(0.034)	(0.038)	(10.294)
age = 30	0.060	0.089	0.011	0.033	0.052	0.070	0.075	0.000	0.003	-0.002	-0.014	-0.005	0.012	10.746	0.470	81.720
	(0.018)	(0.010)	(0.006)	(0.025)	(0.019)	(0.008)	(0.007)	(0.000)	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.029)	(0.040)	(10.015)
age = 35	0.111	0.096	0.017	0.044	0.055	0.082	0.080	0.000	0.010	0.013	0.003	0.011	0.019	10.861	0.516	104.821
	(0.020)	(0.009)	(0.007)	(0.019)	(0.012)	(0.008)	(0.007)	(0.000)	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)	(0.026)	(0.032)	(10.011)
age = 40	0.136	0.081	0.003	0.055	0.062	0.060	0.063	0.000	0.004	0.009	0.009	0.004	0.034	10.973	0.551	94.446
	(0.025)	(0.010)	(0.008)	(0.019)	(0.012)	(0.010)	(0.008)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.027)	(0.036)	(10.422)
age = 45	0.173	0.109	0.031	0.123	0.103	0.069	0.073	0.000	0.018	0.029	0.037	0.020	0.062	11.029	0.651	129.714
	(0.036)	(0.011)	(0.010)	(0.025)	(0.016)	(0.011)	(0.010)	(0.000)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.031)	(0.053)	(10.906)
age = 50	0.208	0.081	0.024	0.214	0.160	0.062	0.059	0.000	0.013	0.018	0.035	0.014	0.115	10.996	0.864	115.915
	(0.055)	(0.016)	(0.015)	(0.035)	(0.026)	(0.014)	(0.014)	(0.000)	(0.015)	(0.013)	(0.014)	(0.015)	(0.020)	(0.040)	(0.087)	(11.900)

Footnote for tables E.1–E.6. AE = Adult Equivalent. Tables E1a and E1b show estimates of variance decompositions for several variables at several ages, based on simulations of 100 lives per PSID sample member. The estimates are for men in the early birth cohort (1935–1944). Bootstrapped standard errors are in parentheses. To compute the contribution to the variance of each source for each age we use the method explained in Section 5.1. Columns 1-13 report the contribution to the variance of the variable indicated by each panel explained by the following factors: (1) education, (2) the wage component μ, (3) the hours component η, (4) the permanent employment component ν (5) the i.i.d shocks to employment status plus variation in initial employment conditional on number of children, marital status, and education, (6) the initial draw and shocks u^{ω} to the autoregressive wage component ω as well as the i.i.d. wage shock, (7) the initial draw ω_{25}^{h} and the shocks u^{h} to ω^{h} plus the i.i.d. hours shocks ε^{h}, (8) the initial draw and shocks to the autoregressive component of unearned income, (9) the random component ε^{ED_s} of spouse's education, (10) the random component $\tilde{\mu}_s$ of μ_s, (11) ν_s and η_s, (12) the random component $\tilde{\omega}_0^s$ of the initial condition ω_0^s and shocks to ω^s over the marriage and (13) the contribution of random variation in marriage histories conditional on $[\mu, \eta, \nu, \omega_{25}, EDUC]$. Columns 14 and 15 report the mean and variance of each row variable across individuals at the indicated age. Column 16 is 100 times the ratio of the sum of columns 1 to 13 divided by column 15. Section 5.1 discusses the simulation methodology. Tables E2–E6 have the same format. E3 and E5 are for men from the baby boom (1945–1962) and later (1964–1974) cohorts, respectively. Tables E2, E4, and E6 are for women from the early, baby boom, and late cohorts, respectively.

Table E.2a: Contributions to Variance of Outcomes at Various Ages - Women Born 1935–1944

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.103	0.077	0.012	-0.007	0.445	0.053	0.118	0.000	-0.002	-0.000	0.000	0.003	0.451	8.261	1.624	77.196
	(0.029)	(0.011)	(0.010)	(0.010)	(0.049)	(0.010)	(0.014)	(0.000)	(0.009)	(0.009)	(0.009)	(0.009)	(0.067)	(0.089)	(0.104)	(4.922)
age = 30	0.078	0.074	0.035	-0.006	0.403	0.074	0.112	0.000	0.015	0.020	0.012	0.009	0.471	8.230	1.735	74.777
	(0.023)	(0.012)	(0.011)	(0.016)	(0.033)	(0.012)	(0.014)	(0.000)	(0.012)	(0.011)	(0.012)	(0.011)	(0.076)	(0.086)	(0.086)	(5.771)
age = 35	0.088	0.086	0.037	0.003	0.409	0.081	0.135	0.000	0.012	0.018	0.016	0.001	0.285	8.621	1.872	62.567
	(0.023)	(0.012)	(0.010)	(0.023)	(0.029)	(0.012)	(0.012)	(0.000)	(0.010)	(0.010)	(0.010)	(0.010)	(0.048)	(0.077)	(0.056)	(4.450)
age = 40	0.113	0.091	0.039	0.249	0.414	0.091	0.159	0.000	-0.002	0.005	0.009	0.003	0.131	9.122	1.859	69.997
	(0.027)	(0.015)	(0.012)	(0.043)	(0.025)	(0.014)	(0.013)	(0.000)	(0.012)	(0.011)	(0.011)	(0.011)	(0.023)	(0.066)	(0.058)	(5.545)
age = 45	0.146	0.080	0.033	0.383	0.441	0.083	0.179	0.000	-0.007	-0.004	-0.013	-0.005	0.056	9.448	1.795	76.417
	(0.030)	(0.017)	(0.014)	(0.039)	(0.027)	(0.017)	(0.015)	(0.000)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.061)	(0.071)	(6.753)
age = 50	0.185	0.111	0.055	0.429	0.538	0.094	0.175	0.000	0.010	0.023	0.012	0.026	0.035	9.492	1.937	87.329
	(0.033)	(0.018)	(0.014)	(0.039)	(0.031)	(0.017)	(0.015)	(0.000)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.064)	(0.081)	(6.412)
Log Family Income																
c1*age = 26*	0.045	0.030	0.009	-0.007	-0.010	0.007	0.020	-0.021	0.009	0.061	0.034	0.055	0.057	10.688	0.541	53.483
	(0.032)	(0.008)	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.016)	(0.008)	(0.019)	(0.072)	(0.100)	(10.732)
age = 30	0.040	0.015	-0.014	0.004	-0.019	0.008	0.011	-0.000	0.016	0.051	0.014	0.055	0.075	10.794	0.518	49.432
	(0.022)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.012)	(0.008)	(0.018)	(0.037)	(0.041)	(8.890)
age = 35	0.061	0.031	0.016	0.031	-0.003	0.015	0.023	0.021	0.032	0.058	0.029	0.061	0.096	10.910	0.549	85.679
	(0.019)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.017)	(0.035)	(0.033)	(9.391)
age = 40	0.070	0.027	0.001	0.034	-0.012	0.015	0.027	0.023	0.030	0.038	0.020	0.049	0.125	11.009	0.575	77.867
	(0.020)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.018)	(0.036)	(0.033)	(9.092)
age = 45	0.086	0.034	0.006	0.035	-0.017	0.019	0.043	0.028	0.023	0.020	0.020	0.035	0.160	11.054	0.628	78.451
	(0.021)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)	(0.019)	(0.037)	(0.035)	(9.745)
age = 50	0.122	0.042	0.009	0.061	-0.011	0.032	0.055	0.060	0.034	0.040	0.031	0.045	0.184	11.034	0.715	98.614
	(0.023)	(0.009)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.020)	(0.038)	(0.040)	(9.532)
Log Family Income AE																
c1*age = 26*	0.099	0.029	0.009	-0.008	0.002	0.012	0.023	-0.017	0.011	0.057	0.039	0.059	0.034	9.881	0.615	56.596
	(0.037)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.010)	(0.019)	(0.009)	(0.009)	(0.074)	(0.119)	(10.100)
age = 30	0.084	0.016	-0.014	-0.001	-0.001	0.015	0.015	0.003	0.020	0.050	0.021	0.057	0.038	9.900	0.579	52.445
	(0.027)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.014)	(0.008)	(0.007)	(0.039)	(0.043)	(8.143)
age = 35	0.104	0.037	0.020	0.026	0.010	0.025	0.025	0.022	0.038	0.060	0.037	0.062	0.043	9.979	0.594	85.517
	(0.023)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.035)	(0.033)	(8.806)
age = 40	0.101	0.030	0.001	0.025	-0.003	0.021	0.030	0.024	0.029	0.036	0.025	0.048	0.037	10.211	0.578	69.765
	(0.022)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.035)	(0.030)	(8.409)
age = 45	0.098	0.037	0.010	0.028	-0.006	0.022	0.038	0.030	0.022	0.020	0.023	0.033	0.042	10.464	0.567	70.134
	(0.021)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.033)	(0.029)	(9.448)
age = 50	0.124	0.040	0.006	0.052	-0.003	0.032	0.048	0.058	0.030	0.035	0.037	0.041	0.043	10.577	0.597	91.025
	(0.021)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.011)	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.032)	(0.033)	(9.443)

Table E.2b: Contributions to Variance of Outcomes at Various Ages - Women Born 1935–1944 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.041	0.066	0.000	0.000	0.001	0.033	-0.000	0.000	0.001	0.001	-0.001	-0.001	0.012	2.421	0.203	75.709
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.055)	(0.014)	(6.598)
age = 30	0.049	0.063	0.002	0.001	0.006	0.051	0.001	0.000	0.003	0.004	0.002	0.003	0.013	2.428	0.234	84.385
	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.038)	(0.011)	(6.484)
age = 35	0.061	0.068	0.004	0.000	0.005	0.057	-0.001	0.000	0.003	0.005	0.002	0.002	0.009	2.487	0.254	84.774
	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.029)	(0.010)	(6.268)
age = 40	0.066	0.074	-0.001	-0.003	0.002	0.062	-0.004	0.000	0.002	0.001	0.001	-0.002	0.004	2.584	0.265	76.568
	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.027)	(0.009)	(5.937)
age = 45	0.068	0.081	-0.001	-0.001	0.003	0.068	-0.003	0.000	-0.001	-0.002	-0.001	-0.002	0.002	2.676	0.267	78.896
	(0.008)	(0.007)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.027)	(0.009)	(5.730)
age = 50	0.066	0.087	0.002	0.001	0.003	0.072	-0.002	0.000	-0.000	-0.002	-0.001	0.001	0.001	2.725	0.266	85.359
	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.028)	(0.009)	(6.315)
Log Hours																
c1*age = 26*	-0.002	0.004	0.013	-0.006	0.210	0.006	0.116	0.000	-0.003	-0.004	-0.002	-0.000	0.249	6.041	0.802	72.598
	(0.013)	(0.004)	(0.006)	(0.005)	(0.023)	(0.005)	(0.012)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.037)	(0.060)	(0.046)	(5.245)
age = 30	-0.011	0.003	0.024	-0.004	0.195	0.012	0.108	0.000	0.004	0.010	0.004	0.002	0.248	6.018	0.825	72.073
	(0.009)	(0.005)	(0.006)	(0.008)	(0.016)	(0.005)	(0.011)	(0.000)	(0.006)	(0.005)	(0.006)	(0.006)	(0.040)	(0.058)	(0.040)	(5.791)
age = 35	-0.007	0.004	0.027	-0.003	0.256	0.007	0.139	0.000	0.011	0.011	0.008	0.001	0.149	6.303	0.911	66.268
	(0.007)	(0.005)	(0.006)	(0.011)	(0.014)	(0.005)	(0.009)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.026)	(0.053)	(0.025)	(4.735)
age = 40	0.012	0.002	0.037	0.122	0.301	0.005	0.167	0.000	-0.001	0.005	0.008	0.005	0.069	6.665	0.910	80.355
	(0.008)	(0.006)	(0.007)	(0.021)	(0.012)	(0.005)	(0.009)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)	(0.044)	(0.025)	(5.471)
age = 45	0.029	-0.007	0.031	0.182	0.308	-0.002	0.180	0.000	-0.004	-0.003	-0.006	0.000	0.031	6.881	0.863	85.782
	(0.011)	(0.006)	(0.008)	(0.019)	(0.013)	(0.006)	(0.009)	(0.000)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.041)	(0.032)	(6.766)
age = 50	0.044	0.002	0.043	0.200	0.340	0.001	0.175	0.000	0.006	0.015	0.003	0.014	0.020	6.896	0.915	94.122
	(0.013)	(0.007)	(0.008)	(0.019)	(0.014)	(0.006)	(0.009)	(0.000)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.043)	(0.035)	(6.523)
Log Family Earnings																
c1*age = 26*	0.059	0.036	0.018	-0.003	0.005	0.006	0.037	0.000	0.009	0.066	0.053	0.061	0.087	10.593	0.714	60.769
	(0.050)	(0.011)	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)	(0.000)	(0.010)	(0.012)	(0.027)	(0.011)	(0.032)	(0.092)	(0.164)	(13.026)
age = 30	0.056	0.010	-0.020	0.042	0.020	-0.001	0.027	0.000	0.021	0.052	0.036	0.063	0.167	10.660	0.751	62.932
	(0.039)	(0.012)	(0.012)	(0.020)	(0.013)	(0.012)	(0.012)	(0.000)	(0.016)	(0.013)	(0.023)	(0.013)	(0.047)	(0.051)	(0.093)	(11.486)
age = 35	0.092	0.040	0.039	0.108	0.052	0.012	0.044	0.000	0.045	0.059	0.037	0.071	0.236	10.734	0.867	96.304
	(0.039)	(0.014)	(0.013)	(0.022)	(0.015)	(0.013)	(0.014)	(0.000)	(0.018)	(0.014)	(0.018)	(0.014)	(0.046)	(0.049)	(0.085)	(12.005)
age = 40	0.115	0.046	0.015	0.129	0.043	0.013	0.058	0.000	0.048	0.046	0.040	0.053	0.252	10.819	0.917	93.604
	(0.041)	(0.014)	(0.013)	(0.022)	(0.015)	(0.013)	(0.015)	(0.000)	(0.016)	(0.014)	(0.017)	(0.014)	(0.038)	(0.048)	(0.079)	(10.757)
age = 45	0.150	0.044	0.019	0.137	0.056	0.037	0.075	0.000	0.038	0.017	0.054	0.047	0.263	10.855	0.997	94.035
	(0.044)	(0.016)	(0.015)	(0.025)	(0.017)	(0.015)	(0.016)	(0.000)	(0.018)	(0.015)	(0.017)	(0.015)	(0.034)	(0.048)	(0.079)	(11.229)
age = 50	0.246	0.067	0.034	0.226	0.120	0.055	0.096	0.000	0.059	0.058	0.091	0.072	0.279	10.773	1.232	113.839
	(0.051)	(0.017)	(0.016)	(0.028)	(0.020)	(0.017)	(0.017)	(0.000)	(0.019)	(0.017)	(0.020)	(0.017)	(0.039)	(0.054)	(0.096)	(10.507)

Table E.3a: Contributions to Variance of Outcomes at Various Ages - Men Born 1945–1962

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.027	0.130	0.017	0.046	0.097	0.061	0.113	0.000	-0.004	0.002	0.000	-0.000	0.005	10.371	0.502	98.529
	(0.010)	(0.010)	(0.005)	(0.009)	(0.013)	(0.007)	(0.006)	(0.000)	(0.005)	(0.004)	(0.004)	(0.004)	(0.001)	(0.017)	(0.023)	(7.034)
age = 30	0.051	0.127	0.020	0.100	0.158	0.101	0.101	0.000	-0.001	-0.004	0.005	-0.007	0.006	10.532	0.614	107.046
	(0.008)	(0.009)	(0.005)	(0.018)	(0.016)	(0.008)	(0.006)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.019)	(0.025)	(6.758)
age = 35	0.098	0.136	0.015	0.139	0.190	0.110	0.097	0.000	-0.004	0.000	-0.010	-0.010	0.007	10.678	0.711	107.945
	(0.012)	(0.011)	(0.006)	(0.023)	(0.019)	(0.009)	(0.007)	(0.000)	(0.007)	(0.006)	(0.006)	(0.006)	(0.001)	(0.020)	(0.032)	(6.834)
age = 40	0.141	0.139	0.017	0.236	0.270	0.123	0.104	0.000	-0.006	-0.000	0.005	-0.003	0.013	10.749	0.860	120.729
	(0.018)	(0.012)	(0.008)	(0.031)	(0.024)	(0.011)	(0.009)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.003)	(0.022)	(0.043)	(6.970)
age = 45	0.177	0.130	0.002	0.379	0.394	0.106	0.102	0.000	-0.014	-0.022	-0.005	-0.015	0.028	10.735	1.107	113.957
	(0.025)	(0.014)	(0.010)	(0.042)	(0.033)	(0.012)	(0.010)	(0.000)	(0.010)	(0.009)	(0.010)	(0.010)	(0.005)	(0.027)	(0.059)	(6.262)
age = 50	0.252	0.142	0.017	0.604	0.606	0.117	0.110	0.000	-0.003	-0.007	0.008	0.004	0.053	10.606	1.562	121.832
	(0.032)	(0.015)	(0.012)	(0.054)	(0.045)	(0.014)	(0.012)	(0.000)	(0.013)	(0.012)	(0.012)	(0.012)	(0.009)	(0.034)	(0.083)	(6.284)
Log Family Income																
c1*age = 26*	0.020	0.084	0.007	0.012	0.015	0.035	0.061	-0.005	0.001	0.010	0.000	0.007	0.046	10.713	0.378	77.826
	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.015)	(0.010)	(5.036)
age = 30	0.044	0.085	0.013	0.027	0.041	0.061	0.054	-0.001	0.006	0.011	0.009	0.010	0.046	10.919	0.434	93.678
	(0.005)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.015)	(0.011)	(5.065)
age = 35	0.069	0.081	0.006	0.032	0.037	0.061	0.048	-0.004	0.004	0.011	0.005	0.006	0.046	11.103	0.459	87.581
	(0.007)	(0.006)	(0.003)	(0.006)	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.016)	(0.013)	(5.336)
age = 40	0.095	0.087	0.009	0.058	0.044	0.072	0.058	-0.000	0.013	0.021	0.018	0.013	0.058	11.226	0.502	109.037
	(0.009)	(0.007)	(0.004)	(0.008)	(0.006)	(0.006)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.016)	(0.017)	(5.777)
age = 45	0.109	0.078	0.007	0.085	0.043	0.058	0.046	0.009	0.011	0.011	0.013	0.010	0.077	11.288	0.561	99.397
	(0.012)	(0.007)	(0.005)	(0.011)	(0.009)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.018)	(0.022)	(6.270)
age = 50	0.140	0.081	0.012	0.135	0.051	0.065	0.060	0.030	0.017	0.018	0.022	0.020	0.110	11.272	0.670	113.893
	(0.015)	(0.008)	(0.005)	(0.014)	(0.012)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.021)	(0.029)	(6.671)
Log Family Income AE																
c1*age = 26*	0.032	0.080	0.009	0.009	0.023	0.032	0.061	-0.003	0.000	0.006	0.002	0.004	0.032	10.162	0.435	66.099
	(0.005)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.016)	(0.011)	(4.629)
age = 30	0.052	0.077	0.013	0.020	0.041	0.058	0.055	-0.001	0.005	0.010	0.013	0.010	0.031	10.226	0.493	77.985
	(0.006)	(0.005)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.017)	(0.011)	(4.300)
age = 35	0.066	0.074	0.007	0.027	0.039	0.060	0.051	-0.003	0.005	0.011	0.012	0.008	0.026	10.305	0.506	75.976
	(0.007)	(0.006)	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.017)	(0.012)	(4.835)
age = 40	0.070	0.074	0.009	0.047	0.046	0.066	0.056	0.001	0.008	0.018	0.022	0.011	0.017	10.447	0.509	87.692
	(0.008)	(0.006)	(0.003)	(0.007)	(0.005)	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.001)	(0.016)	(0.013)	(5.390)
age = 45	0.071	0.070	0.008	0.072	0.052	0.060	0.049	0.011	0.011	0.012	0.022	0.013	0.019	10.612	0.524	89.841
	(0.009)	(0.006)	(0.004)	(0.009)	(0.007)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.017)	(0.016)	(5.799)
age = 50	0.106	0.074	0.012	0.114	0.062	0.062	0.060	0.034	0.016	0.019	0.029	0.020	0.031	10.718	0.593	107.813
	(0.012)	(0.007)	(0.005)	(0.011)	(0.010)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.019)	(0.022)	(6.134)

Table E.3b: Contributions to Variance of Outcomes at Various Ages - Men Born 1945–1962 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.019	0.114	0.002	0.000	0.001	0.053	-0.000	0.000	0.001	0.000	0.000	0.001	0.001	2.787	0.198	97.576
	(0.002)	(0.007)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.010)	(0.005)	(3.807)
age = 30	0.038	0.112	0.001	0.000	0.006	0.092	-0.000	0.000	6.676	-0.000	0.000	-0.000	0.001	2.930	0.267	93.864
	(0.003)	(0.007)	(0.001)	(0.001)	(0.002)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.013)	(0.006)	(3.618)
age = 35	0.062	0.115	0.003	0.000	0.010	0.102	-0.000	0.000	-0.000	0.001	0.000	0.000	0.001	3.072	0.302	97.280
	(0.005)	(0.008)	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.015)	(0.007)	(3.637)
age = 40	0.080	0.118	0.001	0.002	0.011	0.107	0.001	0.000	0.002	0.001	0.002	0.000	0.001	3.172	0.321	102.085
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.015)	(0.008)	(3.875)
age = 45	0.086	0.120	0.001	0.001	0.010	0.107	-0.001	0.000	0.002	-0.001	0.002	-0.000	0.001	3.235	0.325	100.668
	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.016)	(0.009)	(3.496)
age = 50	0.079	0.119	-0.000	-0.002	0.005	0.106	-0.001	0.000	-0.001	-0.001	-0.001	-0.000	0.001	3.274	0.317	95.720
	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.016)	(0.009)	(3.744)
Log Hours																
c1*age = 26*	0.005	0.001	0.016	0.023	0.066	0.001	0.114	0.000	-0.003	0.001	0.001	-0.000	0.001	7.593	0.222	102.405
	(0.005)	(0.002)	(0.003)	(0.005)	(0.008)	(0.002)	(0.005)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.011)	(0.012)	(7.735)
age = 30	0.005	0.001	0.018	0.048	0.085	-0.001	0.105	0.000	0.000	-0.003	0.003	-0.003	0.001	7.615	0.226	114.797
	(0.003)	(0.002)	(0.003)	(0.009)	(0.009)	(0.003)	(0.004)	(0.000)	(0.002)	(0.002)	(0.003)	(0.002)	(0.000)	(0.010)	(0.012)	(8.669)
age = 35	0.011	0.003	0.016	0.062	0.095	-0.001	0.102	0.000	-0.002	-0.001	-0.005	-0.006	0.002	7.625	0.242	114.608
	(0.004)	(0.003)	(0.003)	(0.010)	(0.009)	(0.003)	(0.005)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.010)	(0.014)	(8.539)
age = 40	0.018	0.003	0.016	0.099	0.129	0.002	0.104	0.000	-0.004	-0.001	0.001	-0.002	0.005	7.607	0.288	128.164
	(0.006)	(0.003)	(0.003)	(0.013)	(0.011)	(0.003)	(0.005)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.011)	(0.018)	(8.481)
age = 45	0.030	0.000	0.011	0.154	0.187	-0.004	0.103	0.000	-0.006	-0.008	-0.002	-0.006	0.013	7.553	0.381	124.459
	(0.009)	(0.004)	(0.004)	(0.017)	(0.014)	(0.004)	(0.005)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.014)	(0.024)	(7.175)
age = 50	0.060	0.007	0.016	0.237	0.283	0.003	0.105	0.000	-0.000	-0.002	0.004	0.002	0.024	7.436	0.555	133.170
	(0.012)	(0.005)	(0.005)	(0.021)	(0.018)	(0.005)	(0.006)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.020)	(0.032)	(6.675)
Log Family Earnings																
c1*age = 26*	0.023	0.099	0.012	0.030	0.054	0.042	0.083	0.000	0.001	0.012	-0.000	0.008	0.056	10.614	0.469	89.501
	(0.008)	(0.008)	(0.004)	(0.007)	(0.007)	(0.006)	(0.005)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.017)	(0.018)	(6.461)
age = 30	0.050	0.100	0.017	0.068	0.100	0.072	0.070	0.000	0.006	0.009	0.015	0.007	0.056	10.810	0.542	105.428
	(0.007)	(0.008)	(0.004)	(0.012)	(0.010)	(0.006)	(0.005)	(0.000)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.017)	(0.019)	(6.391)
age = 35	0.080	0.098	0.008	0.085	0.106	0.074	0.065	0.000	0.003	0.012	0.009	0.005	0.058	10.989	0.589	102.427
	(0.010)	(0.009)	(0.005)	(0.015)	(0.011)	(0.007)	(0.006)	(0.000)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.018)	(0.024)	(6.840)
age = 40	0.122	0.105	0.015	0.147	0.141	0.086	0.077	0.000	0.012	0.024	0.029	0.015	0.082	11.107	0.681	125.437
	(0.015)	(0.009)	(0.006)	(0.021)	(0.014)	(0.008)	(0.007)	(0.000)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.019)	(0.032)	(7.299)
age = 45	0.148	0.088	0.006	0.221	0.181	0.066	0.060	0.000	0.001	0.001	0.022	0.005	0.125	11.150	0.831	111.101
	(0.022)	(0.011)	(0.009)	(0.029)	(0.019)	(0.010)	(0.009)	(0.000)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.023)	(0.046)	(7.686)
age = 50	0.226	0.106	0.014	0.370	0.280	0.082	0.086	0.000	0.016	0.025	0.057	0.028	0.214	11.082	1.143	131.753
	(0.029)	(0.013)	(0.011)	(0.037)	(0.027)	(0.013)	(0.011)	(0.000)	(0.012)	(0.011)	(0.012)	(0.011)	(0.021)	(0.030)	(0.067)	(7.686)

Table E.4a: Contributions to Variance of Outcomes at Various Ages - Women Born 1945–1962

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.281	0.108	0.032	0.057	0.340	0.061	0.183	0.000	0.004	0.000	-0.002	0.011	0.175	9.135	1.609	77.720
	(0.028)	(0.011)	(0.007)	(0.009)	(0.019)	(0.008)	(0.010)	(0.000)	(0.006)	(0.006)	(0.005)	(0.006)	(0.022)	(0.039)	(0.039)	(2.913)
age = 30	0.082	0.093	0.026	0.234	0.396	0.082	0.167	0.000	-0.000	0.000	0.005	-0.005	0.162	9.231	1.753	70.839
	(0.014)	(0.011)	(0.008)	(0.019)	(0.016)	(0.010)	(0.009)	(0.000)	(0.007)	(0.007)	(0.006)	(0.007)	(0.016)	(0.035)	(0.033)	(3.329)
age = 35	0.080	0.117	0.025	0.401	0.439	0.103	0.188	0.000	0.004	-0.002	0.012	0.010	0.086	9.434	1.737	84.286
	(0.013)	(0.013)	(0.009)	(0.021)	(0.017)	(0.012)	(0.010)	(0.000)	(0.007)	(0.008)	(0.008)	(0.007)	(0.011)	(0.033)	(0.040)	(3.524)
age = 40	0.092	0.114	0.025	0.509	0.477	0.096	0.183	0.000	0.002	0.000	0.013	-0.001	0.035	9.679	1.681	91.932
	(0.015)	(0.013)	(0.010)	(0.023)	(0.018)	(0.013)	(0.011)	(0.000)	(0.008)	(0.008)	(0.009)	(0.009)	(0.007)	(0.032)	(0.044)	(4.243)
age = 45	0.109	0.123	0.023	0.575	0.544	0.108	0.187	0.000	0.006	0.007	0.006	0.009	0.016	9.826	1.732	98.921
	(0.017)	(0.014)	(0.010)	(0.026)	(0.021)	(0.014)	(0.011)	(0.000)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.032)	(0.050)	(4.090)
age = 50	0.147	0.132	0.033	0.615	0.653	0.112	0.174	0.000	0.002	0.005	0.011	0.008	0.010	9.804	1.949	97.590
	(0.020)	(0.014)	(0.010)	(0.029)	(0.025)	(0.013)	(0.011)	(0.000)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.036)	(0.057)	(4.060)
Log Family Income																
c1*age = 26*	0.026	0.045	0.005	0.007	-0.013	0.016	0.050	0.006	0.003	0.043	0.002	0.041	0.152	10.673	0.559	68.513
	(0.009)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.012)	(0.018)	(0.018)	(5.051)
age = 30	0.047	0.045	0.005	0.039	-0.004	0.024	0.044	0.018	0.018	0.046	0.008	0.040	0.145	10.846	0.593	79.993
	(0.007)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)	(0.016)	(0.016)	(5.388)
age = 35	0.070	0.048	0.010	0.055	-0.003	0.031	0.045	0.027	0.031	0.050	0.019	0.047	0.150	11.010	0.612	94.752
	(0.008)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)	(0.017)	(0.016)	(5.357)
age = 40	0.079	0.040	-0.001	0.057	-0.009	0.024	0.043	0.023	0.032	0.040	0.011	0.031	0.170	11.119	0.640	84.400
	(0.010)	(0.006)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.010)	(0.018)	(0.018)	(5.243)
age = 45	0.111	0.056	0.015	0.081	0.003	0.038	0.055	0.026	0.033	0.044	0.024	0.034	0.198	11.158	0.711	100.930
	(0.012)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.012)	(0.020)	(0.022)	(5.481)
age = 50	0.121	0.062	0.013	0.090	-0.010	0.044	0.054	0.043	0.037	0.041	0.026	0.035	0.215	11.125	0.794	96.925
	(0.014)	(0.007)	(0.005)	(0.010)	(0.008)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.014)	(0.022)	(0.027)	(5.450)
Log Family Income AE																
c1*age = 26*	0.085	0.048	0.005	0.007	-0.008	0.020	0.051	0.006	0.009	0.041	0.006	0.040	0.025	10.018	0.567	59.093
	(0.010)	(0.005)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.018)	(0.017)	(4.799)
age = 30	0.075	0.046	0.006	0.033	-0.001	0.027	0.044	0.017	0.019	0.043	0.014	0.040	0.037	10.088	0.604	66.181
	(0.007)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.018)	(0.014)	(5.048)
age = 35	0.083	0.051	0.010	0.047	0.002	0.035	0.044	0.027	0.030	0.046	0.024	0.047	0.049	10.184	0.604	82.339
	(0.008)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.018)	(0.014)	(5.064)
age = 40	0.067	0.044	0.000	0.051	0.001	0.026	0.042	0.025	0.028	0.039	0.015	0.031	0.054	10.375	0.578	73.133
	(0.008)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.017)	(0.014)	(5.062)
age = 45	0.073	0.059	0.014	0.071	0.015	0.039	0.053	0.030	0.028	0.040	0.031	0.035	0.057	10.578	0.585	93.521
	(0.009)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)	(0.015)	(5.485)
age = 50	0.091	0.063	0.015	0.080	0.011	0.044	0.054	0.046	0.031	0.040	0.036	0.035	0.060	10.666	0.634	95.662
	(0.010)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.018)	(0.019)	(5.640)

Table E.4b: Contributions to Variance of Outcomes at Various Ages - Women Born 1945–1962 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.035	0.078	-0.001	-0.001	-0.000	0.037	0.000	0.000	-0.000	-0.001	-0.000	-0.000	0.002	2.509	0.192	78.018
	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.014)	(0.006)	(3.422)
age = 30	0.047	0.082	-0.001	-0.001	0.003	0.062	0.000	0.000	0.000	-0.001	0.001	0.000	0.003	2.620	0.241	81.615
	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)	(0.006)	(3.352)
age = 35	0.058	0.087	-0.000	0.002	0.003	0.070	0.002	0.000	0.001	4.441	0.002	0.001	0.003	2.710	0.262	87.422
	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.016)	(0.006)	(3.466)
age = 40	0.062	0.093	0.001	0.005	0.005	0.076	0.002	0.000	0.001	0.001	0.002	0.001	0.001	2.797	0.268	93.261
	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.017)	(0.006)	(3.569)
age = 45	0.062	0.097	-0.000	0.004	0.005	0.079	0.001	0.000	0.001	0.000	0.002	-0.001	0.000	2.871	0.268	93.086
	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.017)	(0.006)	(3.666)
age = 50	0.064	0.101	0.002	0.004	0.004	0.082	0.002	0.000	0.000	0.002	0.001	0.001	0.000	2.914	0.270	97.741
	(0.006)	(0.008)	(0.001)	(0.002)	(0.001)	(0.008)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.018)	(0.007)	(3.646)
Log Hours																
c1*age = 26*	0.115	0.005	0.032	0.030	0.259	0.005	0.181	0.000	0.001	0.001	-0.003	0.005	0.113	6.723	0.873	85.327
	(0.013)	(0.003)	(0.005)	(0.005)	(0.010)	(0.003)	(0.009)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.014)	(0.028)	(0.019)	(2.852)
age = 30	0.014	-0.003	0.028	0.110	0.259	-0.001	0.170	0.000	-0.004	-0.000	0.000	-0.003	0.095	6.729	0.869	76.532
	(0.005)	(0.003)	(0.006)	(0.009)	(0.008)	(0.003)	(0.007)	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.024)	(0.015)	(3.257)
age = 35	0.014	0.005	0.030	0.184	0.278	0.006	0.184	0.000	0.000	-0.001	0.004	0.005	0.047	6.843	0.829	91.220
	(0.004)	(0.004)	(0.006)	(0.010)	(0.008)	(0.004)	(0.007)	(0.000)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)	(0.022)	(0.016)	(3.382)
age = 40	0.020	0.002	0.030	0.229	0.290	-0.001	0.184	0.000	0.000	0.002	0.005	0.000	0.020	6.992	0.782	99.886
	(0.005)	(0.004)	(0.006)	(0.010)	(0.008)	(0.004)	(0.008)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.021)	(0.019)	(4.080)
age = 45	0.022	0.004	0.030	0.256	0.313	0.004	0.187	0.000	0.003	0.005	0.002	0.006	0.010	7.068	0.782	107.801
	(0.006)	(0.004)	(0.006)	(0.011)	(0.010)	(0.004)	(0.007)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.020)	(0.021)	(3.975)
age = 50	0.030	0.006	0.032	0.267	0.355	0.004	0.175	0.000	-0.000	0.002	0.003	0.003	0.008	7.031	0.855	103.362
	(0.007)	(0.004)	(0.006)	(0.012)	(0.011)	(0.004)	(0.008)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.022)	(0.024)	(3.921)
Log Family Earnings																
c1*age = 26*	0.077	0.062	0.009	0.023	0.037	0.026	0.084	0.000	0.007	0.056	0.008	0.051	0.239	10.528	0.827	82.162
	(0.024)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.000)	(0.006)	(0.008)	(0.006)	(0.007)	(0.023)	(0.024)	(0.045)	(5.772)
age = 30	0.094	0.051	0.005	0.130	0.071	0.028	0.071	0.000	0.022	0.054	0.017	0.045	0.263	10.669	0.924	92.088
	(0.016)	(0.009)	(0.008)	(0.014)	(0.009)	(0.008)	(0.008)	(0.000)	(0.009)	(0.009)	(0.008)	(0.008)	(0.019)	(0.022)	(0.039)	(6.585)
age = 35	0.137	0.068	0.017	0.189	0.090	0.040	0.080	0.000	0.047	0.062	0.040	0.058	0.303	10.813	1.017	111.365
	(0.018)	(0.010)	(0.009)	(0.017)	(0.011)	(0.009)	(0.009)	(0.000)	(0.010)	(0.009)	(0.009)	(0.009)	(0.020)	(0.022)	(0.041)	(6.430)
age = 40	0.141	0.051	-0.004	0.206	0.097	0.026	0.085	0.000	0.047	0.051	0.025	0.033	0.316	10.930	1.049	102.453
	(0.021)	(0.010)	(0.010)	(0.020)	(0.011)	(0.010)	(0.010)	(0.000)	(0.011)	(0.009)	(0.009)	(0.009)	(0.019)	(0.023)	(0.042)	(6.658)
age = 45	0.168	0.069	0.015	0.254	0.136	0.043	0.090	0.000	0.041	0.053	0.041	0.041	0.328	10.965	1.147	111.504
	(0.024)	(0.011)	(0.010)	(0.022)	(0.013)	(0.011)	(0.010)	(0.000)	(0.012)	(0.011)	(0.011)	(0.010)	(0.022)	(0.025)	(0.048)	(6.426)
age = 50	0.211	0.090	0.020	0.308	0.173	0.056	0.083	0.000	0.049	0.054	0.069	0.046	0.354	10.889	1.367	110.774
	(0.028)	(0.012)	(0.010)	(0.025)	(0.016)	(0.011)	(0.012)	(0.000)	(0.013)	(0.011)	(0.014)	(0.011)	(0.028)	(0.029)	(0.060)	(6.161)

Table E.5a: Contributions to Variance of Outcomes at Various Ages - Men Born 1964–1974

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.003	0.144	0.029	0.110	0.193	0.065	0.115	0.000	0.012	0.002	-0.001	0.007	0.006	10.305	0.653	104.940
	(0.020)	(0.012)	(0.008)	(0.016)	(0.019)	(0.011)	(0.009)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.002)	(0.020)	(0.037)	(10.172)
age = 30	0.095	0.141	0.012	0.301	0.333	0.115	0.098	0.000	-0.004	-0.002	-0.005	-0.001	0.011	10.467	0.933	117.357
	(0.022)	(0.015)	(0.011)	(0.036)	(0.028)	(0.012)	(0.012)	(0.000)	(0.012)	(0.012)	(0.011)	(0.011)	(0.002)	(0.024)	(0.051)	(8.953)
age = 35	0.145	0.147	0.013	0.437	0.399	0.111	0.092	0.000	-0.008	-0.004	-0.008	0.010	0.017	10.602	1.150	117.418
	(0.030)	(0.016)	(0.013)	(0.045)	(0.034)	(0.015)	(0.014)	(0.000)	(0.013)	(0.014)	(0.014)	(0.014)	(0.004)	(0.028)	(0.064)	(8.588)
age = 40	0.227	0.155	0.035	0.537	0.485	0.124	0.086	0.000	0.003	-0.003	0.004	0.014	0.023	10.649	1.367	123.637
	(0.038)	(0.018)	(0.015)	(0.053)	(0.041)	(0.017)	(0.016)	(0.000)	(0.015)	(0.015)	(0.016)	(0.016)	(0.005)	(0.033)	(0.075)	(8.435)
age = 45	0.313	0.155	0.030	0.640	0.561	0.138	0.096	0.000	0.003	-0.000	0.018	0.014	0.044	10.612	1.592	126.436
	(0.045)	(0.018)	(0.016)	(0.057)	(0.051)	(0.018)	(0.016)	(0.000)	(0.016)	(0.016)	(0.016)	(0.016)	(0.007)	(0.040)	(0.090)	(7.579)
age = 50	0.343	0.139	0.021	0.690	0.612	0.141	0.098	0.000	0.007	-0.012	0.011	-0.005	0.063	10.507	1.792	117.610
	(0.050)	(0.019)	(0.017)	(0.061)	(0.071)	(0.018)	(0.017)	(0.000)	(0.017)	(0.016)	(0.017)	(0.016)	(0.011)	(0.056)	(0.137)	(7.964)
Log Family Income																
c1*age = 26*	0.010	0.087	0.010	0.029	0.019	0.034	0.061	-0.002	-0.001	0.014	0.002	0.012	0.090	10.713	0.474	77.193
	(0.009)	(0.008)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.019)	(0.017)	(7.885)
age = 30	0.059	0.089	0.004	0.086	0.061	0.064	0.053	0.004	0.005	0.012	0.006	0.015	0.091	10.945	0.579	94.603
	(0.011)	(0.008)	(0.006)	(0.012)	(0.010)	(0.007)	(0.006)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.018)	(0.021)	(8.181)
age = 35	0.097	0.094	0.008	0.124	0.067	0.064	0.050	-0.001	0.011	0.019	0.009	0.019	0.089	11.111	0.645	100.544
	(0.015)	(0.009)	(0.007)	(0.016)	(0.012)	(0.008)	(0.008)	(0.004)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.020)	(0.027)	(9.015)
age = 40	0.150	0.090	0.014	0.155	0.079	0.069	0.052	-0.000	0.015	0.024	0.014	0.025	0.103	11.202	0.724	108.869
	(0.019)	(0.010)	(0.008)	(0.018)	(0.014)	(0.010)	(0.008)	(0.005)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.023)	(0.032)	(9.030)
age = 45	0.184	0.088	0.003	0.187	0.076	0.066	0.045	-0.003	0.010	0.021	0.017	0.022	0.135	11.229	0.806	105.732
	(0.023)	(0.010)	(0.009)	(0.021)	(0.017)	(0.010)	(0.009)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.028)	(0.040)	(8.326)
age = 50	0.218	0.084	0.018	0.213	0.089	0.075	0.056	0.020	0.026	0.030	0.024	0.033	0.169	11.193	0.896	117.585
	(0.027)	(0.011)	(0.010)	(0.023)	(0.019)	(0.011)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)	(0.035)	(0.055)	(8.916)
Log Family Income AE																
c1*age = 26*	0.027	0.087	0.012	0.026	0.030	0.035	0.062	0.003	0.005	0.012	0.006	0.012	0.008	10.279	0.461	70.454
	(0.009)	(0.007)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.019)	(0.016)	(7.394)
age = 30	0.068	0.081	0.004	0.070	0.059	0.059	0.054	0.006	0.004	0.009	0.013	0.013	0.013	10.348	0.577	78.327
	(0.011)	(0.007)	(0.005)	(0.011)	(0.009)	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)	(0.005)	(0.006)	(0.003)	(0.020)	(0.019)	(7.081)
age = 35	0.090	0.083	0.003	0.103	0.067	0.063	0.053	0.002	0.009	0.017	0.016	0.014	0.021	10.385	0.649	83.036
	(0.014)	(0.008)	(0.006)	(0.013)	(0.011)	(0.008)	(0.007)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)	(0.002)	(0.021)	(0.023)	(7.910)
age = 40	0.124	0.081	0.016	0.131	0.081	0.071	0.056	0.004	0.017	0.024	0.021	0.022	0.027	10.461	0.697	96.657
	(0.016)	(0.009)	(0.007)	(0.015)	(0.013)	(0.009)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)	(0.003)	(0.022)	(0.026)	(8.170)
age = 45	0.127	0.074	0.000	0.148	0.077	0.064	0.046	0.003	0.006	0.018	0.024	0.020	0.036	10.564	0.716	89.794
	(0.018)	(0.009)	(0.008)	(0.017)	(0.014)	(0.009)	(0.008)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.004)	(0.024)	(0.031)	(8.029)
age = 50	0.162	0.072	0.013	0.173	0.091	0.071	0.056	0.026	0.021	0.028	0.033	0.030	0.048	10.651	0.757	108.677
	(0.021)	(0.010)	(0.008)	(0.018)	(0.016)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.031)	(0.043)	(8.565)

Table E.5b: Contributions to Variance of Outcomes at Various Ages - Men Born 1964–1974 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.013	0.114	0.001	0.000	0.000	0.053	-0.002	0.000	0.001	-0.001	0.000	-0.000	0.001	2.778	0.193	94.008
	(0.002)	(0.007)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.011)	(0.005)	(5.331)
age = 30	0.030	0.115	0.000	0.001	0.003	0.095	-0.001	0.000	0.001	-0.000	0.000	-0.001	0.001	2.966	0.257	94.827
	(0.003)	(0.008)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.013)	(0.006)	(5.254)
age = 35	0.052	0.119	0.002	0.002	0.003	0.107	-0.000	0.000	0.002	0.001	0.002	-0.000	0.001	3.128	0.289	100.328
	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.015)	(0.007)	(4.848)
age = 40	0.065	0.119	0.003	-0.001	0.005	0.108	0.000	0.000	0.002	-0.001	0.002	0.000	0.001	3.226	0.304	99.868
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.017)	(0.008)	(5.122)
age = 45	0.074	0.123	0.002	0.001	0.006	0.111	0.003	0.000	0.004	0.003	0.005	0.002	0.001	3.269	0.312	106.664
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.018)	(0.008)	(5.116)
age = 50	0.066	0.119	-0.001	-0.001	0.003	0.109	0.000	0.000	0.001	0.000	0.000	-0.001	0.001	3.270	0.306	96.906
	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.022)	(0.008)	(5.177)
Log Hours																
c1*age = 26*	-0.003	0.003	0.023	0.057	0.130	-0.000	0.116	0.000	0.005	0.002	-0.000	0.003	0.002	7.548	0.297	113.565
	(0.010)	(0.004)	(0.004)	(0.008)	(0.013)	(0.004)	(0.006)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.013)	(0.019)	(10.843)
age = 30	0.032	0.004	0.015	0.142	0.187	0.002	0.104	0.000	-0.001	0.001	-0.002	0.001	0.003	7.544	0.372	131.427
	(0.010)	(0.005)	(0.005)	(0.017)	(0.015)	(0.005)	(0.006)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.013)	(0.024)	(10.122)
age = 35	0.038	0.006	0.015	0.186	0.207	-0.006	0.100	0.000	-0.003	-0.001	-0.004	0.007	0.006	7.534	0.427	128.771
	(0.012)	(0.006)	(0.005)	(0.019)	(0.015)	(0.005)	(0.007)	(0.000)	(0.006)	(0.006)	(0.006)	(0.006)	(0.001)	(0.016)	(0.028)	(9.693)
age = 40	0.061	0.007	0.022	0.219	0.234	0.000	0.095	0.000	-0.001	0.000	0.001	0.004	0.010	7.503	0.490	133.226
	(0.015)	(0.006)	(0.006)	(0.022)	(0.017)	(0.006)	(0.007)	(0.000)	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)	(0.018)	(0.030)	(9.298)
age = 45	0.086	0.006	0.018	0.250	0.264	0.004	0.097	0.000	-0.002	-0.002	0.004	0.003	0.019	7.445	0.563	132.692
	(0.016)	(0.006)	(0.006)	(0.023)	(0.020)	(0.006)	(0.007)	(0.000)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.022)	(0.036)	(8.220)
age = 50	0.097	0.002	0.016	0.265	0.285	0.008	0.098	0.000	0.001	-0.006	0.001	-0.003	0.027	7.365	0.638	124.131
	(0.018)	(0.006)	(0.006)	(0.024)	(0.029)	(0.006)	(0.008)	(0.000)	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)	(0.035)	(0.053)	(8.472)
Log Family Earnings																
c1*age = 26*	0.011	0.106	0.015	0.080	0.115	0.039	0.086	0.000	0.003	0.017	-0.002	0.016	0.114	10.600	0.644	93.190
	(0.019)	(0.011)	(0.008)	(0.014)	(0.013)	(0.010)	(0.009)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.022)	(0.034)	(9.949)
age = 30	0.081	0.104	-0.003	0.213	0.200	0.075	0.066	0.000	-0.000	0.014	-0.001	0.012	0.123	10.820	0.827	106.954
	(0.019)	(0.012)	(0.011)	(0.028)	(0.021)	(0.011)	(0.010)	(0.000)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.022)	(0.043)	(9.372)
age = 35	0.139	0.111	0.009	0.300	0.225	0.066	0.061	0.000	-0.004	0.012	0.007	0.018	0.129	10.980	0.956	112.090
	(0.027)	(0.014)	(0.013)	(0.036)	(0.024)	(0.013)	(0.013)	(0.000)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.026)	(0.055)	(9.552)
age = 40	0.222	0.099	0.036	0.368	0.268	0.078	0.065	0.000	0.022	0.028	0.035	0.033	0.160	11.062	1.114	126.943
	(0.036)	(0.016)	(0.014)	(0.041)	(0.028)	(0.015)	(0.015)	(0.000)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.030)	(0.066)	(9.393)
age = 45	0.309	0.112	0.022	0.453	0.300	0.082	0.075	0.000	0.023	0.022	0.043	0.025	0.224	11.071	1.297	130.297
	(0.043)	(0.017)	(0.016)	(0.046)	(0.034)	(0.017)	(0.016)	(0.000)	(0.016)	(0.016)	(0.016)	(0.016)	(0.020)	(0.035)	(0.080)	(9.131)
age = 50	0.353	0.096	0.024	0.502	0.328	0.078	0.066	0.000	0.029	0.024	0.047	0.026	0.292	11.007	1.491	125.153
	(0.051)	(0.019)	(0.017)	(0.050)	(0.043)	(0.018)	(0.017)	(0.000)	(0.018)	(0.017)	(0.019)	(0.017)	(0.032)	(0.048)	(0.114)	(9.346)

Table E.6a: Contributions to Variance of Outcomes at Various Ages - Women Born 1964–1974

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.170	0.130	0.029	0.122	0.354	0.060	0.182	0.000	0.001	-0.008	-0.004	-0.002	0.050	9.609	1.404	77.066
	(0.037)	(0.015)	(0.010)	(0.014)	(0.023)	(0.011)	(0.013)	(0.000)	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.041)	(0.055)	(5.446)
age = 30	0.092	0.113	0.021	0.360	0.490	0.089	0.165	0.000	-0.015	-0.017	-0.005	-0.001	0.074	9.620	1.773	77.168
	(0.019)	(0.016)	(0.012)	(0.023)	(0.023)	(0.013)	(0.014)	(0.000)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.037)	(0.046)	(5.344)
age = 35	0.113	0.125	0.040	0.482	0.567	0.098	0.162	0.000	0.006	-0.007	-0.007	0.005	0.060	9.673	1.952	84.215
	(0.019)	(0.016)	(0.013)	(0.027)	(0.025)	(0.015)	(0.014)	(0.000)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.038)	(0.050)	(5.066)
age = 40	0.120	0.140	0.033	0.577	0.612	0.101	0.165	0.000	-0.004	-0.008	0.006	0.015	0.019	9.789	1.994	89.070
	(0.021)	(0.017)	(0.014)	(0.030)	(0.027)	(0.017)	(0.014)	(0.000)	(0.013)	(0.013)	(0.012)	(0.012)	(0.007)	(0.039)	(0.054)	(5.324)
age = 45	0.135	0.109	0.023	0.652	0.658	0.098	0.139	0.000	-0.012	-0.020	-0.014	-0.007	0.004	9.894	2.040	86.463
	(0.025)	(0.017)	(0.015)	(0.033)	(0.031)	(0.018)	(0.016)	(0.000)	(0.014)	(0.014)	(0.014)	(0.013)	(0.004)	(0.043)	(0.067)	(5.683)
age = 50	0.155	0.128	0.009	0.662	0.716	0.093	0.135	0.000	-0.007	-0.020	0.009	-0.011	0.015	9.878	2.188	86.115
	(0.029)	(0.018)	(0.014)	(0.040)	(0.045)	(0.017)	(0.016)	(0.000)	(0.014)	(0.014)	(0.014)	(0.014)	(0.009)	(0.058)	(0.104)	(5.712)
Log Family Income																
c1*age = 26*	0.026	0.067	0.012	0.026	-0.001	0.022	0.067	0.000	0.004	0.029	0.003	0.032	0.210	10.702	0.650	76.775
	(0.012)	(0.008)	(0.005)	(0.006)	(0.008)	(0.007)	(0.006)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.014)	(0.024)	(0.023)	(6.654)
age = 30	0.071	0.063	0.013	0.065	0.014	0.033	0.057	0.013	0.021	0.046	0.025	0.042	0.178	10.921	0.687	93.051
	(0.010)	(0.008)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.004)	(0.007)	(0.007)	(0.006)	(0.007)	(0.011)	(0.018)	(0.019)	(7.184)
age = 35	0.082	0.055	0.009	0.072	0.005	0.040	0.048	0.021	0.027	0.051	0.022	0.049	0.166	11.087	0.702	92.313
	(0.012)	(0.008)	(0.006)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.019)	(0.021)	(7.297)
age = 40	0.116	0.068	0.013	0.087	0.000	0.044	0.058	0.020	0.039	0.050	0.031	0.046	0.190	11.161	0.763	99.768
	(0.015)	(0.009)	(0.007)	(0.010)	(0.009)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)	(0.023)	(0.026)	(7.602)
age = 45	0.153	0.075	0.020	0.132	0.006	0.049	0.062	0.021	0.052	0.052	0.035	0.055	0.236	11.167	0.877	108.230
	(0.019)	(0.010)	(0.009)	(0.013)	(0.011)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.017)	(0.027)	(0.035)	(7.990)
age = 50	0.165	0.076	0.014	0.156	0.004	0.050	0.066	0.027	0.053	0.037	0.042	0.040	0.318	11.090	1.045	100.154
	(0.023)	(0.011)	(0.010)	(0.018)	(0.015)	(0.011)	(0.010)	(0.008)	(0.012)	(0.011)	(0.010)	(0.011)	(0.030)	(0.036)	(0.058)	(7.869)
Log Family Income AE																
c1*age = 26*	0.065	0.069	0.012	0.023	-0.001	0.022	0.062	0.000	0.006	0.024	0.006	0.029	0.039	10.155	0.603	59.300
	(0.014)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.024)	(0.023)	(6.767)
age = 30	0.084	0.063	0.011	0.057	0.008	0.035	0.053	0.012	0.019	0.039	0.030	0.043	0.039	10.231	0.662	74.477
	(0.011)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.022)	(0.017)	(6.875)
age = 35	0.080	0.055	0.010	0.062	0.008	0.038	0.046	0.021	0.023	0.043	0.031	0.046	0.049	10.294	0.672	76.018
	(0.011)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)	(0.005)	(0.022)	(0.018)	(6.992)
age = 40	0.086	0.064	0.013	0.073	0.010	0.041	0.053	0.023	0.033	0.045	0.040	0.041	0.060	10.407	0.683	85.176
	(0.012)	(0.008)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.022)	(0.020)	(7.232)
age = 45	0.095	0.070	0.019	0.107	0.020	0.046	0.056	0.024	0.042	0.043	0.041	0.046	0.078	10.547	0.724	94.960
	(0.014)	(0.009)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)	(0.005)	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.023)	(0.025)	(7.992)
age = 50	0.118	0.075	0.012	0.130	0.034	0.048	0.061	0.031	0.043	0.033	0.049	0.038	0.118	10.615	0.830	95.162
	(0.018)	(0.010)	(0.008)	(0.014)	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.017)	(0.031)	(0.044)	(7.862)

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Table E.6b: Contributions to Variance of Outcomes at Various Ages - Women Born 1964–1974 Continued

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Wages																
c1*age = 26*	0.025	0.091	-0.003	-0.003	-0.003	0.042	-0.002	0.000	-0.002	-0.003	-0.001	-0.002	0.000	2.635	0.186	74.471
	(0.004)	(0.008)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.015)	(0.006)	(4.908)
age = 30	0.045	0.093	-0.002	0.002	0.003	0.071	-0.000	0.000	-0.002	-0.000	0.000	-0.002	0.001	2.782	0.245	85.229
	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.016)	(0.006)	(5.194)
age = 35	0.054	0.094	-0.003	0.001	0.002	0.076	-0.003	0.000	-0.002	-0.003	-0.000	-0.004	0.002	2.871	0.264	80.809
	(0.005)	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.019)	(0.006)	(4.898)
age = 40	0.059	0.100	0.000	0.004	0.004	0.081	0.001	0.000	-0.002	-0.000	0.003	-0.000	0.001	2.932	0.269	93.410
	(0.005)	(0.008)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.020)	(0.006)	(5.179)
age = 45	0.058	0.102	-0.002	0.005	0.006	0.083	-0.000	0.000	-0.001	0.000	0.002	0.000	0.000	2.983	0.267	94.965
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.021)	(0.007)	(5.188)
age = 50	0.060	0.102	-0.002	0.006	0.003	0.083	0.000	0.000	-0.002	-0.000	8.643	-0.002	0.000	3.006	0.267	92.993
	(0.006)	(0.008)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.024)	(0.007)	(5.149)
Log Hours																
c1*age = 26*	0.069	0.009	0.032	0.064	0.265	0.003	0.190	0.000	0.001	0.000	-0.002	0.001	0.035	7.054	0.749	89.002
	(0.018)	(0.005)	(0.007)	(0.007)	(0.014)	(0.005)	(0.010)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.028)	(0.028)	(5.287)
age = 30	0.020	0.001	0.029	0.164	0.298	0.000	0.172	0.000	-0.005	-0.005	-0.005	0.002	0.045	6.960	0.840	85.309
	(0.007)	(0.005)	(0.007)	(0.010)	(0.010)	(0.005)	(0.009)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.023)	(0.021)	(5.053)
age = 35	0.024	0.006	0.035	0.205	0.319	-0.001	0.168	0.000	0.003	-0.003	-0.006	0.004	0.033	6.949	0.874	90.168
	(0.007)	(0.005)	(0.007)	(0.011)	(0.010)	(0.005)	(0.008)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.021)	(4.907)
age = 40	0.022	0.010	0.031	0.242	0.338	-0.001	0.168	0.000	-0.001	-0.003	-0.001	0.005	0.010	7.004	0.867	94.564
	(0.007)	(0.005)	(0.007)	(0.012)	(0.011)	(0.005)	(0.009)	(0.000)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.023)	(0.022)	(5.130)
age = 45	0.027	-0.005	0.027	0.268	0.353	-0.002	0.157	0.000	-0.006	-0.007	-0.008	-0.000	0.004	7.060	0.870	93.082
	(0.008)	(0.005)	(0.007)	(0.013)	(0.013)	(0.006)	(0.009)	(0.000)	(0.006)	(0.006)	(0.006)	(0.005)	(0.002)	(0.026)	(0.027)	(5.608)
age = 50	0.028	0.003	0.019	0.268	0.377	-0.005	0.151	0.000	-0.006	-0.008	0.002	-0.004	0.009	7.038	0.920	90.716
	(0.010)	(0.006)	(0.007)	(0.017)	(0.019)	(0.006)	(0.010)	(0.000)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.038)	(0.041)	(5.832)
Log Family Earnings																
c1*age = 26*	0.068	0.093	0.028	0.080	0.101	0.034	0.107	0.000	0.007	0.047	0.013	0.047	0.294	10.555	0.962	95.381
	(0.030)	(0.011)	(0.009)	(0.011)	(0.011)	(0.011)	(0.010)	(0.000)	(0.009)	(0.010)	(0.009)	(0.009)	(0.025)	(0.031)	(0.056)	(7.730)
age = 30	0.137	0.086	0.013	0.190	0.127	0.047	0.089	0.000	0.030	0.050	0.043	0.046	0.285	10.753	1.075	106.424
	(0.022)	(0.013)	(0.011)	(0.019)	(0.014)	(0.012)	(0.012)	(0.000)	(0.013)	(0.012)	(0.012)	(0.012)	(0.020)	(0.023)	(0.045)	(8.155)
age = 35	0.166	0.075	0.019	0.228	0.123	0.048	0.078	0.000	0.049	0.054	0.035	0.051	0.313	10.902	1.179	105.169
	(0.027)	(0.014)	(0.013)	(0.021)	(0.014)	(0.013)	(0.013)	(0.000)	(0.014)	(0.013)	(0.014)	(0.013)	(0.022)	(0.025)	(0.049)	(8.083)
age = 40	0.226	0.102	0.039	0.282	0.163	0.067	0.101	0.000	0.074	0.064	0.067	0.064	0.358	10.968	1.312	122.492
	(0.032)	(0.016)	(0.015)	(0.025)	(0.016)	(0.015)	(0.015)	(0.000)	(0.016)	(0.015)	(0.017)	(0.015)	(0.025)	(0.029)	(0.058)	(8.331)
age = 45	0.266	0.093	0.030	0.365	0.202	0.073	0.098	0.000	0.084	0.056	0.068	0.070	0.417	10.968	1.490	122.288
	(0.037)	(0.017)	(0.017)	(0.029)	(0.020)	(0.016)	(0.016)	(0.000)	(0.018)	(0.017)	(0.017)	(0.016)	(0.032)	(0.035)	(0.072)	(8.332)
age = 50	0.276	0.109	0.030	0.407	0.241	0.054	0.100	0.000	0.095	0.052	0.095	0.049	0.528	10.857	1.784	114.235
	(0.041)	(0.019)	(0.018)	(0.037)	(0.025)	(0.018)	(0.018)	(0.000)	(0.021)	(0.019)	(0.019)	(0.018)	(0.059)	(0.048)	(0.117)	(8.090)

Table E.7: Percent Contributions to Variance of Outcomes at Various Ages - Men Born 1935–1944

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	6.057	27.319	5.113	10.141	15.616	12.682	24.881	0.000	1.332	-0.591	0.177	2.555	0.487	10.528	0.455	105.769
	(4.652)	(3.399)	(1.559)	(3.583)	(5.017)	(2.219)	(3.007)	(0.000)	(1.452)	(1.528)	(1.493)	(1.519)	(0.267)	(0.034)	(0.054)	(11.722)
age = 30	12.778	18.850	3.248	10.597	16.210	16.855	17.675	0.000	0.403	-1.457	-2.493	-1.743	0.465	10.614	0.537	91.386
	(3.203)	(2.575)	(1.430)	(5.209)	(3.995)	(2.284)	(2.293)	(0.000)	(1.407)	(1.397)	(1.430)	(1.424)	(0.158)	(0.029)	(0.057)	(11.051)
age = 35	21.749	19.732	3.991	11.177	15.986	17.756	16.453	0.000	1.297	0.577	-0.045	0.862	0.890	10.678	0.605	110.426
	(3.203)	(2.248)	(1.363)	(3.874)	(2.373)	(2.034)	(1.839)	(0.000)	(1.487)	(1.363)	(1.404)	(1.460)	(0.219)	(0.027)	(0.045)	(10.865)
age = 40	24.653	15.370	0.790	14.034	18.497	13.498	13.382	0.000	-0.034	-1.432	-0.680	-1.510	1.578	10.714	0.681	98.147
	(3.598)	(2.187)	(1.537)	(3.452)	(2.258)	(1.958)	(1.873)	(0.000)	(1.487)	(1.463)	(1.531)	(1.503)	(0.346)	(0.030)	(0.052)	(11.376)
age = 45	26.511	15.805	4.022	25.173	26.368	12.740	11.254	0.000	0.287	1.043	0.437	1.381	1.538	10.693	0.866	126.560
	(4.409)	(2.071)	(1.554)	(3.213)	(2.667)	(1.896)	(1.796)	(0.000)	(1.583)	(1.520)	(1.540)	(1.502)	(0.533)	(0.036)	(0.081)	(10.665)
age = 50	24.503	8.743	2.160	32.359	32.338	7.776	6.087	0.000	-0.373	-1.033	0.293	-1.738	2.445	10.586	1.238	113.560
	(4.818)	(1.908)	(1.571)	(3.322)	(3.766)	(1.678)	(1.698)	(0.000)	(1.379)	(1.407)	(1.401)	(1.434)	(0.659)	(0.049)	(0.132)	(11.117)
Log Family Earnings																
c1*age = 26*	7.913	26.877	5.664	8.033	11.239	12.421	23.597	0.000	0.895	0.590	0.555	3.847	2.203	10.634	0.406	103.834
	(4.221)	(2.872)	(1.360)	(2.963)	(3.562)	(1.962)	(2.459)	(0.000)	(1.284)	(1.335)	(1.315)	(1.361)	(0.591)	(0.034)	(0.038)	(10.294)
age = 30	12.700	18.918	2.424	7.098	11.151	14.924	15.947	0.000	0.554	-0.390	-2.984	-1.099	2.476	10.746	0.470	81.720
	(2.698)	(2.235)	(1.267)	(4.299)	(3.024)	(1.900)	(1.850)	(0.000)	(1.310)	(1.326)	(1.278)	(1.264)	(0.455)	(0.029)	(0.040)	(10.015)
age = 35	21.486	18.634	3.363	8.465	10.558	15.818	15.556	0.000	2.006	2.568	0.577	2.076	3.714	10.861	0.516	104.821
	(2.743)	(1.930)	(1.247)	(3.158)	(1.891)	(1.710)	(1.510)	(0.000)	(1.357)	(1.311)	(1.305)	(1.344)	(0.618)	(0.026)	(0.032)	(10.011)
age = 40	24.700	14.715	0.511	9.910	11.286	10.844	11.443	0.000	0.810	1.640	1.620	0.759	6.208	10.973	0.551	94.446
	(3.041)	(1.880)	(1.446)	(2.825)	(1.866)	(1.733)	(1.571)	(0.000)	(1.404)	(1.399)	(1.406)	(1.383)	(0.854)	(0.027)	(0.036)	(10.422)
age = 45	26.581	16.668	4.736	18.844	15.775	10.523	11.212	0.000	2.701	4.376	5.753	3.001	9.543	11.029	0.651	129.714
	(3.767)	(1.916)	(1.539)	(2.804)	(2.302)	(1.734)	(1.618)	(0.000)	(1.623)	(1.515)	(1.641)	(1.496)	(1.196)	(0.031)	(0.053)	(10.906)
age = 50	24.076	9.384	2.730	24.735	18.491	7.203	6.785	0.000	1.524	2.031	4.042	1.606	13.308	10.996	0.864	115.915
	(4.496)	(1.953)	(1.659)	(2.893)	(3.063)	(1.722)	(1.703)	(0.000)	(1.673)	(1.465)	(1.577)	(1.634)	(1.457)	(0.040)	(0.087)	(11.900)
Log Family Income AE																
c1*age = 26*	11.482	20.144	3.779	3.873	5.589	8.922	17.599	-2.264	0.827	1.698	0.883	2.943	13.944	9.982	0.471	89.418
	(2.152)	(1.719)	(0.980)	(1.675)	(1.800)	(1.316)	(1.425)	(0.425)	(0.960)	(1.034)	(0.912)	(0.992)	(1.544)	(0.033)	(0.023)	(7.534)
age = 30	16.328	15.056	3.370	3.141	5.160	12.302	13.471	-2.009	0.455	0.287	-0.501	0.697	10.779	9.996	0.525	78.536
	(2.028)	(1.471)	(0.933)	(2.231)	(1.518)	(1.241)	(1.083)	(0.416)	(0.983)	(0.998)	(0.894)	(0.942)	(1.163)	(0.032)	(0.024)	(7.417)
age = 35	22.256	14.345	3.158	3.150	5.009	13.125	11.436	-1.255	1.266	2.622	0.120	1.960	6.894	10.057	0.530	84.085
	(2.243)	(1.410)	(0.965)	(1.603)	(1.230)	(1.176)	(1.065)	(0.412)	(0.957)	(0.960)	(1.026)	(0.981)	(0.937)	(0.031)	(0.022)	(7.577)
age = 40	22.240	11.598	-0.573	1.879	3.347	10.036	9.892	-1.287	0.600	0.666	0.192	-0.018	3.088	10.249	0.499	61.661
	(2.437)	(1.360)	(1.050)	(1.485)	(1.376)	(1.244)	(1.131)	(0.539)	(1.023)	(1.051)	(1.055)	(1.055)	(0.615)	(0.030)	(0.022)	(8.134)
age = 45	23.093	14.727	2.887	8.277	5.014	10.235	10.355	0.987	1.960	2.548	3.018	1.847	2.420	10.484	0.490	87.369
	(2.644)	(1.425)	(1.108)	(1.724)	(1.723)	(1.268)	(1.162)	(0.786)	(1.100)	(1.132)	(1.208)	(1.097)	(0.419)	(0.028)	(0.023)	(8.610)
age = 50	23.606	11.100	0.933	11.630	3.268	9.633	8.654	5.836	0.648	3.587	3.954	1.028	3.089	10.640	0.510	86.966
	(3.024)	(1.556)	(1.205)	(1.815)	(2.247)	(1.373)	(1.264)	(1.246)	(1.267)	(1.249)	(1.213)	(1.279)	(0.667)	(0.025)	(0.029)	(9.661)

Footnote for tables E.7–E.12. AE = Adult Equivalent. Table E.7 shows estimates of variance decompositions for several variables at several ages, based on simulations of 100 lives per PSID sample member. The estimates are for men in the early birth cohort (1935–1944). Bootstrapped standard errors are in parentheses. To compute the percent contribution to the variance of each source for each age we use the method explained in Section 5.1. Columns 1-13 report the contribution to the variance of the variable indicated by each panel explained by the following factors: (1) education, (2) the wage component μ, (3) the hours component η, (4) the permanent employment component ν (5) the i.i.d shocks to employment status, (6) the initial draw and shocks u^{ω} to the autoregressive wage component ω as well as the i.i.d. wage shock, (7) the initial draw ω^{h}_{25} and the shocks u^{h} to ω^{h} plus the i.i.d. hours shocks ε^{h}, (8) the initial draw and shocks to the autoregressive component of unearned income, (9) the random component ε^{ED_s} of spouse's education, (10) the random component $\tilde{\mu}_s$ of μ_s, (11) ν_s and η_s, (12) the random component $\tilde{\omega}^{s}_{0}$ of the initial condition ω^{s}_{0} and shocks to ω^{s} over the marriage and (13) the contribution of random variation in marriage histories conditional on $[\mu, \eta, \nu, \omega_{25}, EDUC]$. Columns 14 and 15 report the mean and standard deviation of each row variable across individuals at the indicated age. Column 16 is the sum of the percent contributions. Section 5.1 discusses the simulation methodology. Tables E.8–E.12 have the same format. E.9 and E.11 are for men from the baby boom (1945–1962) and later (1964–1974) cohorts, respectively. Tables E.8, E.10, and E.12 are for women from the early, baby boom, and late cohorts, respectively.

Table E.8: Percent Contributions to Variance of Outcomes at Various Ages - Women Born 1935–1944

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	6.326	4.771	0.751	-0.415	27.379	3.275	7.253	0.000	-0.136	-0.020	0.011	0.198	27.801	8.261	1.624	77.196
	(1.746)	(0.724)	(0.603)	(0.645)	(2.423)	(0.647)	(0.998)	(0.000)	(0.566)	(0.559)	(0.584)	(0.587)	(3.752)	(0.089)	(0.104)	(4.922)
age = 30	4.481	4.244	2.022	-0.325	23.207	4.260	6.471	0.000	0.888	1.165	0.704	0.509	27.151	8.230	1.735	74.777
	(1.305)	(0.710)	(0.622)	(0.949)	(2.029)	(0.680)	(0.810)	(0.000)	(0.674)	(0.622)	(0.670)	(0.662)	(4.072)	(0.086)	(0.086)	(5.771)
age = 35	4.720	4.577	1.973	0.181	21.876	4.318	7.192	0.000	0.654	0.984	0.847	0.039	15.208	8.621	1.872	62.567
	(1.175)	(0.673)	(0.559)	(1.243)	(1.562)	(0.656)	(0.721)	(0.000)	(0.556)	(0.533)	(0.531)	(0.549)	(2.395)	(0.077)	(0.056)	(4.450)
age = 40	6.079	4.912	2.108	13.392	22.246	4.878	8.564	0.000	-0.096	0.260	0.482	0.148	7.024	9.122	1.859	69.997
	(1.378)	(0.816)	(0.630)	(2.524)	(1.247)	(0.746)	(0.788)	(0.000)	(0.625)	(0.595)	(0.603)	(0.616)	(1.175)	(0.066)	(0.058)	(5.545)
age = 45	8.108	4.451	1.860	21.358	24.562	4.602	9.997	0.000	-0.417	-0.233	-0.740	-0.264	3.134	9.448	1.795	76.417
	(1.623)	(0.949)	(0.760)	(2.644)	(1.362)	(0.953)	(0.966)	(0.000)	(0.746)	(0.706)	(0.744)	(0.729)	(0.721)	(0.061)	(0.071)	(6.753)
age = 50	9.551	5.752	2.826	22.133	27.747	4.839	9.046	0.000	0.530	1.168	0.601	1.329	1.806	9.492	1.937	87.329
	(1.668)	(0.932)	(0.744)	(2.546)	(1.421)	(0.885)	(0.904)	(0.000)	(0.725)	(0.746)	(0.737)	(0.700)	(0.685)	(0.064)	(0.081)	(6.412)
Log Family Earnings																
c1*age = 26*	8.284	5.035	2.507	-0.453	0.734	0.884	5.200	0.000	1.261	9.206	7.438	8.534	12.140	10.593	0.714	60.769
	(5.385)	(1.620)	(1.305)	(1.622)	(1.535)	(1.392)	(1.528)	(0.000)	(1.359)	(2.502)	(2.739)	(2.380)	(5.074)	(0.092)	(0.164)	(13.026)
age = 30	7.474	1.301	-2.642	5.606	2.620	-0.070	3.648	0.000	2.801	6.941	4.737	8.327	22.188	10.660	0.751	62.932
	(4.188)	(1.521)	(1.445)	(2.082)	(1.557)	(1.465)	(1.474)	(0.000)	(1.811)	(1.937)	(2.651)	(1.908)	(4.327)	(0.051)	(0.093)	(11.486)
age = 35	10.601	4.591	4.520	12.436	6.016	1.352	5.131	0.000	5.230	6.803	4.295	8.158	27.172	10.734	0.867	96.304
	(3.823)	(1.586)	(1.425)	(2.057)	(1.588)	(1.438)	(1.521)	(0.000)	(1.904)	(1.800)	(1.964)	(1.743)	(3.566)	(0.049)	(0.085)	(12.005)
age = 40	12.523	5.042	1.604	14.031	4.673	1.455	6.309	0.000	5.275	5.061	4.397	5.738	27.497	10.819	0.917	93.604
	(3.743)	(1.536)	(1.409)	(1.900)	(1.528)	(1.424)	(1.482)	(0.000)	(1.711)	(1.536)	(1.749)	(1.628)	(3.025)	(0.048)	(0.079)	(10.757)
age = 45	15.001	4.398	1.868	13.710	5.576	3.758	7.551	0.000	3.836	1.733	5.465	4.721	26.418	10.855	0.997	94.035
	(3.638)	(1.566)	(1.471)	(2.057)	(1.643)	(1.493)	(1.479)	(0.000)	(1.699)	(1.485)	(1.681)	(1.537)	(2.880)	(0.048)	(0.079)	(11.229)
age = 50	19.966	5.425	2.751	18.336	9.747	4.434	7.819	0.000	4.791	4.723	7.362	5.861	22.624	10.773	1.232	113.839
	(3.511)	(1.393)	(1.369)	(1.975)	(1.558)	(1.366)	(1.319)	(0.000)	(1.545)	(1.404)	(1.781)	(1.388)	(2.981)	(0.054)	(0.096)	(10.507)
Log Family Income AE																
c1*age = 26*	16.186	4.730	1.470	-1.345	0.387	1.886	3.667	-2.830	1.743	9.202	6.301	9.663	5.536	9.881	0.615	56.596
	(3.747)	(1.370)	(1.128)	(1.178)	(1.426)	(1.171)	(1.270)	(1.012)	(1.211)	(2.280)	(2.370)	(2.113)	(1.185)	(0.074)	(0.119)	(10.100)
age = 30	14.569	2.792	-2.391	-0.235	-0.193	2.522	2.586	0.554	3.468	8.710	3.636	9.798	6.630	9.900	0.579	52.445
	(3.407)	(1.188)	(0.985)	(1.108)	(1.179)	(1.032)	(1.069)	(1.224)	(1.262)	(1.601)	(2.100)	(1.481)	(1.147)	(0.039)	(0.043)	(8.143)
age = 35	17.493	6.227	3.324	4.354	1.702	4.213	4.147	3.733	6.341	10.049	6.255	10.460	7.218	9.979	0.594	85.517
	(3.097)	(1.199)	(1.044)	(1.224)	(1.107)	(1.088)	(1.076)	(1.248)	(1.260)	(1.489)	(1.436)	(1.363)	(1.150)	(0.035)	(0.033)	(8.806)
age = 40	17.529	5.202	0.209	4.266	-0.578	3.625	5.177	4.179	4.971	6.274	4.276	8.273	6.361	10.211	0.578	69.765
	(3.070)	(1.147)	(1.093)	(1.177)	(1.103)	(1.118)	(1.069)	(1.083)	(1.199)	(1.251)	(1.212)	(1.235)	(1.102)	(0.035)	(0.030)	(8.409)
age = 45	17.383	6.618	1.756	4.962	-1.046	3.932	6.770	5.226	3.797	3.457	4.073	5.794	7.413	10.464	0.567	70.134
	(2.989)	(1.361)	(1.177)	(1.372)	(1.331)	(1.283)	(1.223)	(1.112)	(1.240)	(1.371)	(1.333)	(1.250)	(1.206)	(0.033)	(0.029)	(9.448)
age = 50	20.747	6.759	0.955	8.656	-0.516	5.377	7.983	9.764	5.011	5.892	6.217	6.937	7.243	10.577	0.597	91.025
	(2.836)	(1.373)	(1.221)	(1.447)	(1.334)	(1.328)	(1.185)	(1.476)	(1.304)	(1.291)	(1.384)	(1.244)	(1.446)	(0.032)	(0.033)	(9.443)

Table E.9: Percent Contributions to Variance of Outcomes at Various Ages - Men Born 1945–1962

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	5.441	25.919	3.343	9.192	19.251	12.240	22.482	0.000	-0.721	0.459	0.047	-0.068	0.945	10.371	0.502	98.529
	(1.937)	(2.052)	(0.933)	(1.574)	(1.834)	(1.499)	(1.407)	(0.000)	(0.919)	(0.867)	(0.843)	(0.823)	(0.219)	(0.017)	(0.023)	(7.034)
age = 30	8.237	20.633	3.309	16.263	25.794	16.402	16.509	0.000	-0.103	-0.709	0.759	-1.089	1.039	10.532	0.614	107.046
	(1.262)	(1.578)	(0.833)	(2.333)	(1.868)	(1.350)	(1.093)	(0.000)	(0.870)	(0.888)	(0.873)	(0.832)	(0.172)	(0.019)	(0.025)	(6.758)
age = 35	13.784	19.068	2.166	19.586	26.772	15.412	13.614	0.000	-0.624	0.014	-1.382	-1.458	0.993	10.678	0.711	107.945
	(1.531)	(1.592)	(0.895)	(2.392)	(1.816)	(1.378)	(1.077)	(0.000)	(0.913)	(0.841)	(0.864)	(0.884)	(0.182)	(0.020)	(0.032)	(6.834)
age = 40	16.424	16.119	1.947	27.428	31.367	14.260	12.151	0.000	-0.719	-0.029	0.630	-0.372	1.525	10.749	0.860	120.729
	(1.775)	(1.430)	(0.896)	(2.520)	(1.978)	(1.407)	(1.131)	(0.000)	(0.936)	(0.943)	(0.895)	(0.923)	(0.268)	(0.022)	(0.043)	(6.970)
age = 45	16.015	11.746	0.216	34.201	35.551	9.602	9.198	0.000	-1.238	-1.980	-0.495	-1.367	2.508	10.735	1.107	113.957
	(1.960)	(1.306)	(0.893)	(2.536)	(2.371)	(1.136)	(0.992)	(0.000)	(0.890)	(0.827)	(0.877)	(0.864)	(0.399)	(0.027)	(0.059)	(6.262)
age = 50	16.122	9.079	1.063	38.662	38.809	7.508	7.061	0.000	-0.221	-0.445	0.535	0.238	3.422	10.606	1.562	121.832
	(1.892)	(1.040)	(0.763)	(2.668)	(2.753)	(0.985)	(0.842)	(0.000)	(0.823)	(0.801)	(0.779)	(0.791)	(0.525)	(0.034)	(0.083)	(6.284)
Log Family Earnings																
c1*age = 26*	4.833	21.226	2.465	6.395	11.524	9.050	17.626	0.000	0.240	2.525	-0.073	1.731	11.960	10.614	0.469	89.501
	(1.707)	(1.627)	(0.850)	(1.293)	(1.248)	(1.263)	(1.042)	(0.000)	(0.851)	(0.859)	(0.765)	(0.812)	(0.773)	(0.017)	(0.018)	(6.461)
age = 30	9.292	18.517	3.196	12.499	18.436	13.298	12.977	0.000	1.090	1.731	2.752	1.235	10.403	10.810	0.542	105.428
	(1.143)	(1.388)	(0.767)	(1.936)	(1.464)	(1.140)	(0.964)	(0.000)	(0.850)	(0.884)	(0.859)	(0.813)	(0.630)	(0.017)	(0.019)	(6.391)
age = 35	13.666	16.653	1.379	14.371	18.018	12.492	10.957	0.000	0.514	2.007	1.603	0.899	9.868	10.989	0.589	102.427
	(1.481)	(1.460)	(0.893)	(2.062)	(1.451)	(1.197)	(0.942)	(0.000)	(0.904)	(0.880)	(0.857)	(0.912)	(0.611)	(0.018)	(0.024)	(6.840)
age = 40	17.841	15.348	2.216	21.501	20.734	12.684	11.282	0.000	1.729	3.578	4.296	2.247	11.981	11.107	0.681	125.437
	(1.793)	(1.377)	(0.927)	(2.260)	(1.652)	(1.238)	(1.040)	(0.000)	(0.946)	(1.059)	(1.036)	(0.988)	(0.679)	(0.019)	(0.032)	(7.299)
age = 45	17.784	10.576	0.669	26.589	21.824	7.973	7.185	0.000	0.112	0.143	2.601	0.565	15.080	11.150	0.831	111.101
	(2.047)	(1.335)	(1.028)	(2.353)	(2.034)	(1.134)	(1.078)	(0.000)	(0.998)	(1.026)	(1.078)	(1.048)	(0.810)	(0.023)	(0.046)	(7.686)
age = 50	19.801	9.258	1.252	32.361	24.513	7.177	7.527	0.000	1.439	2.156	5.020	2.482	18.767	11.082	1.143	131.753
	(2.062)	(1.183)	(0.954)	(2.429)	(2.358)	(1.128)	(1.021)	(0.000)	(1.057)	(0.956)	(1.029)	(0.970)	(1.003)	(0.030)	(0.067)	(7.686)
Log Family Income AE																
c1*age = 26*	7.326	18.319	2.018	2.130	5.216	7.412	14.060	-0.667	0.011	1.451	0.538	0.997	7.289	10.162	0.435	66.099
	(1.176)	(1.254)	(0.605)	(0.673)	(0.786)	(1.013)	(0.740)	(0.388)	(0.586)	(0.599)	(0.568)	(0.569)	(0.818)	(0.016)	(0.011)	(4.629)
age = 30	10.634	15.586	2.715	4.051	8.395	11.775	11.202	-0.192	0.958	2.021	2.623	1.941	6.276	10.226	0.493	77.985
	(1.036)	(1.058)	(0.543)	(0.886)	(0.790)	(0.823)	(0.660)	(0.374)	(0.560)	(0.584)	(0.574)	(0.546)	(0.549)	(0.017)	(0.011)	(4.300)
age = 35	13.084	14.681	1.315	5.389	7.652	11.932	10.168	-0.584	1.050	2.132	2.429	1.529	5.199	10.305	0.506	75.976
	(1.211)	(1.114)	(0.619)	(0.974)	(0.796)	(0.875)	(0.653)	(0.375)	(0.637)	(0.637)	(0.636)	(0.639)	(0.401)	(0.017)	(0.012)	(4.835)
age = 40	13.689	14.626	1.729	9.242	9.103	13.004	11.035	0.278	1.530	3.539	4.365	2.146	3.405	10.447	0.509	87.692
	(1.314)	(1.149)	(0.662)	(1.216)	(0.989)	(1.025)	(0.706)	(0.430)	(0.690)	(0.727)	(0.725)	(0.683)	(0.254)	(0.016)	(0.013)	(5.390)
age = 45	13.529	13.435	1.555	13.777	9.923	11.413	9.309	2.141	2.047	2.366	4.125	2.502	3.718	10.612	0.524	89.841
	(1.473)	(1.201)	(0.779)	(1.441)	(1.353)	(0.973)	(0.788)	(0.630)	(0.755)	(0.798)	(0.758)	(0.742)	(0.339)	(0.017)	(0.016)	(5.799)
age = 50	17.945	12.406	2.076	19.208	10.512	10.519	10.098	5.663	2.663	3.229	4.918	3.329	5.248	10.718	0.593	107.813
	(1.621)	(1.116)	(0.767)	(1.570)	(1.683)	(1.035)	(0.823)	(0.856)	(0.861)	(0.835)	(0.823)	(0.801)	(0.551)	(0.019)	(0.022)	(6.134)

Table E.10: Percent Contributions to Variance of Outcomes at Various Ages - Women Born 1945–1962

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	17.451	6.720	1.983	3.567	21.161	3.815	11.344	0.000	0.251	0.007	-0.129	0.688	10.862	9.135	1.609	77.720
	(1.596)	(0.676)	(0.435)	(0.604)	(1.029)	(0.516)	(0.732)	(0.000)	(0.350)	(0.352)	(0.322)	(0.359)	(1.291)	(0.039)	(0.039)	(2.913)
age = 30	4.673	5.330	1.459	13.326	22.580	4.666	9.517	0.000	-0.028	0.028	0.280	-0.262	9.268	9.231	1.753	70.839
	(0.779)	(0.629)	(0.461)	(1.211)	(0.850)	(0.540)	(0.576)	(0.000)	(0.403)	(0.378)	(0.366)	(0.386)	(0.877)	(0.035)	(0.033)	(3.329)
age = 35	4.613	6.723	1.452	23.086	25.295	5.957	10.809	0.000	0.212	-0.104	0.710	0.573	4.959	9.434	1.737	84.286
	(0.754)	(0.751)	(0.530)	(1.326)	(0.865)	(0.649)	(0.607)	(0.000)	(0.421)	(0.441)	(0.450)	(0.409)	(0.623)	(0.033)	(0.040)	(3.524)
age = 40	5.446	6.805	1.512	30.264	28.343	5.727	10.888	0.000	0.092	0.013	0.778	-0.034	2.098	9.679	1.681	91.932
	(0.857)	(0.800)	(0.596)	(1.282)	(1.002)	(0.787)	(0.722)	(0.000)	(0.498)	(0.497)	(0.523)	(0.520)	(0.386)	(0.032)	(0.044)	(4.243)
age = 45	6.312	7.094	1.302	33.218	31.401	6.243	10.787	0.000	0.323	0.425	0.358	0.549	0.909	9.826	1.732	98.921
	(0.977)	(0.832)	(0.595)	(1.332)	(1.112)	(0.809)	(0.688)	(0.000)	(0.535)	(0.509)	(0.512)	(0.530)	(0.270)	(0.032)	(0.050)	(4.090)
age = 50	7.554	6.799	1.697	31.544	33.506	5.755	8.905	0.000	0.110	0.267	0.561	0.397	0.496	9.804	1.949	97.590
	(0.993)	(0.760)	(0.527)	(1.549)	(1.194)	(0.687)	(0.678)	(0.000)	(0.482)	(0.472)	(0.454)	(0.490)	(0.253)	(0.036)	(0.057)	(4.060)
Log Family Earnings																
c1*age = 26*	9.268	7.524	1.096	2.820	4.468	3.121	10.167	0.000	0.850	6.728	1.027	6.194	28.899	10.528	0.827	82.162
	(2.499)	(0.966)	(0.728)	(0.821)	(0.858)	(0.858)	(0.938)	(0.000)	(0.746)	(0.962)	(0.721)	(0.912)	(1.449)	(0.024)	(0.045)	(5.772)
age = 30	10.203	5.468	0.526	14.090	7.682	3.013	7.714	0.000	2.335	5.811	1.885	4.899	28.462	10.669	0.924	92.088
	(1.506)	(0.942)	(0.888)	(1.182)	(0.983)	(0.915)	(0.924)	(0.000)	(0.997)	(0.937)	(0.875)	(0.927)	(1.102)	(0.022)	(0.039)	(6.585)
age = 35	13.482	6.708	1.696	18.576	8.882	3.895	7.892	0.000	4.640	6.120	3.970	5.683	29.820	10.813	1.017	111.365
	(1.616)	(0.960)	(0.851)	(1.265)	(1.058)	(0.919)	(0.901)	(0.000)	(0.992)	(0.935)	(0.853)	(0.868)	(1.046)	(0.022)	(0.041)	(6.430)
age = 40	13.418	4.862	-0.420	19.617	9.292	2.518	8.117	0.000	4.498	4.862	2.422	3.130	30.136	10.930	1.049	102.453
	(1.733)	(0.977)	(0.914)	(1.457)	(1.000)	(0.985)	(0.906)	(0.000)	(1.035)	(0.889)	(0.888)	(0.891)	(1.025)	(0.023)	(0.042)	(6.658)
age = 45	14.653	6.018	1.292	22.164	11.816	3.750	7.852	0.000	3.593	4.600	3.597	3.586	28.584	10.965	1.147	111.504
	(1.777)	(0.982)	(0.856)	(1.448)	(1.077)	(0.922)	(0.875)	(0.000)	(0.984)	(0.911)	(0.967)	(0.876)	(1.109)	(0.025)	(0.048)	(6.426)
age = 50	15.467	6.583	1.438	22.559	12.692	4.113	6.099	0.000	3.567	3.971	5.031	3.369	25.884	10.889	1.367	110.774
	(1.808)	(0.884)	(0.764)	(1.518)	(1.117)	(0.825)	(0.881)	(0.000)	(0.942)	(0.800)	(1.032)	(0.842)	(1.302)	(0.029)	(0.060)	(6.161)
Log Family Income AE																
c1*age = 26*	14.955	8.547	0.870	1.271	-1.398	3.520	9.033	1.027	1.581	7.179	1.047	7.115	4.345	10.018	0.567	59.093
	(1.429)	(0.892)	(0.595)	(0.581)	(0.807)	(0.775)	(0.762)	(0.607)	(0.592)	(0.880)	(0.613)	(0.763)	(0.571)	(0.018)	(0.017)	(4.799)
age = 30	12.506	7.692	0.913	5.513	-0.238	4.518	7.216	2.764	3.158	7.183	2.257	6.627	6.071	10.088	0.604	66.181
	(1.071)	(0.816)	(0.647)	(0.672)	(0.783)	(0.732)	(0.650)	(0.596)	(0.686)	(0.805)	(0.595)	(0.782)	(0.468)	(0.018)	(0.014)	(5.048)
age = 35	13.737	8.513	1.738	7.777	0.360	5.745	7.353	4.481	5.051	7.687	3.975	7.815	8.107	10.184	0.604	82.339
	(1.118)	(0.834)	(0.605)	(0.682)	(0.885)	(0.767)	(0.670)	(0.618)	(0.707)	(0.841)	(0.671)	(0.730)	(0.588)	(0.018)	(0.014)	(5.064)
age = 40	11.515	7.624	0.083	8.851	0.086	4.506	7.332	4.319	4.791	6.716	2.653	5.400	9.256	10.375	0.578	73.133
	(1.172)	(0.887)	(0.644)	(0.829)	(0.885)	(0.799)	(0.725)	(0.595)	(0.781)	(0.798)	(0.662)	(0.753)	(0.667)	(0.017)	(0.014)	(5.062)
age = 45	12.548	10.143	2.375	12.177	2.614	6.666	9.140	5.095	4.768	6.842	5.298	6.036	9.819	10.578	0.585	93.521
	(1.342)	(0.930)	(0.691)	(0.965)	(0.911)	(0.905)	(0.709)	(0.663)	(0.773)	(0.820)	(0.814)	(0.786)	(0.794)	(0.017)	(0.015)	(5.485)
age = 50	14.365	9.934	2.337	12.634	1.772	7.002	8.576	7.297	4.930	6.259	5.664	5.475	9.415	10.666	0.634	95.662
	(1.431)	(0.933)	(0.729)	(1.061)	(1.037)	(0.885)	(0.772)	(0.844)	(0.802)	(0.792)	(0.866)	(0.799)	(0.953)	(0.018)	(0.019)	(5.640)

Table E.11: Percent Contributions to Variance of Outcomes at Various Ages - Men Born 1964–1974

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	0.424	22.031	4.418	16.864	29.513	9.976	17.668	0.000	1.850	0.361	-0.104	1.045	0.893	10.305	0.653	104.940
	(3.026)	(2.064)	(1.213)	(2.205)	(1.735)	(1.693)	(1.583)	(0.000)	(1.250)	(1.212)	(1.222)	(1.197)	(0.231)	(0.020)	(0.037)	(10.172)
age = 30	10.209	15.126	1.271	32.254	35.654	12.354	10.450	0.000	-0.436	-0.167	-0.484	-0.062	1.187	10.467	0.933	117.357
	(2.189)	(1.670)	(1.203)	(2.736)	(2.393)	(1.445)	(1.339)	(0.000)	(1.254)	(1.256)	(1.156)	(1.189)	(0.225)	(0.024)	(0.051)	(8.953)
age = 35	12.583	12.818	1.124	37.980	34.732	9.632	7.994	0.000	-0.712	-0.377	-0.695	0.887	1.451	10.602	1.150	117.418
	(2.388)	(1.519)	(1.098)	(2.692)	(2.640)	(1.384)	(1.291)	(0.000)	(1.144)	(1.214)	(1.195)	(1.193)	(0.272)	(0.028)	(0.064)	(8.588)
age = 40	16.617	11.359	2.587	39.283	35.460	9.063	6.280	0.000	0.203	-0.191	0.267	0.991	1.718	10.649	1.367	123.637
	(2.542)	(1.375)	(1.079)	(2.814)	(2.840)	(1.294)	(1.234)	(0.000)	(1.129)	(1.081)	(1.140)	(1.163)	(0.336)	(0.033)	(0.075)	(8.435)
age = 45	19.657	9.728	1.892	40.197	35.271	8.678	6.017	0.000	0.200	-0.003	1.119	0.891	2.790	10.612	1.592	126.436
	(2.551)	(1.212)	(1.024)	(2.985)	(2.935)	(1.188)	(1.074)	(0.000)	(0.972)	(0.986)	(1.011)	(1.006)	(0.441)	(0.040)	(0.090)	(7.579)
age = 50	19.140	7.751	1.179	38.497	34.133	7.883	5.473	0.000	0.371	-0.680	0.597	-0.271	3.537	10.507	1.792	117.610
	(2.555)	(1.223)	(0.955)	(3.404)	(2.983)	(1.135)	(1.051)	(0.000)	(0.945)	(0.917)	(0.959)	(0.889)	(0.547)	(0.056)	(0.137)	(7.964)
Log Family Earnings																
c1*age = 26*	1.767	16.430	2.301	12.367	17.902	6.045	13.332	0.000	0.454	2.688	-0.259	2.456	17.707	10.600	0.644	93.190
	(2.906)	(1.714)	(1.215)	(1.865)	(1.442)	(1.494)	(1.352)	(0.000)	(1.282)	(1.212)	(1.197)	(1.156)	(0.907)	(0.022)	(0.034)	(9.949)
age = 30	9.845	12.607	-0.350	25.715	24.231	9.122	7.925	0.000	-0.022	1.645	-0.070	1.441	14.866	10.820	0.827	106.954
	(2.129)	(1.548)	(1.251)	(2.507)	(2.112)	(1.343)	(1.286)	(0.000)	(1.314)	(1.293)	(1.293)	(1.276)	(0.693)	(0.022)	(0.043)	(9.372)
age = 35	14.577	11.558	0.889	31.399	23.473	6.874	6.431	0.000	-0.424	1.211	0.719	1.913	13.469	10.980	0.956	112.090
	(2.418)	(1.480)	(1.307)	(2.565)	(2.324)	(1.369)	(1.367)	(0.000)	(1.304)	(1.326)	(1.298)	(1.349)	(0.724)	(0.026)	(0.055)	(9.552)
age = 40	19.905	8.893	3.271	33.078	24.017	6.987	5.796	0.000	1.967	2.536	3.181	2.963	14.351	11.062	1.114	126.943
	(2.671)	(1.459)	(1.234)	(2.678)	(2.498)	(1.385)	(1.353)	(0.000)	(1.315)	(1.228)	(1.326)	(1.354)	(0.772)	(0.030)	(0.066)	(9.393)
age = 45	23.817	8.629	1.679	34.962	23.105	6.329	5.800	0.000	1.793	1.686	3.304	1.956	17.237	11.071	1.297	130.297
	(2.694)	(1.379)	(1.263)	(2.867)	(2.614)	(1.295)	(1.233)	(0.000)	(1.220)	(1.207)	(1.255)	(1.255)	(0.863)	(0.035)	(0.080)	(9.131)
age = 50	23.689	6.469	1.594	33.699	22.002	5.222	4.438	0.000	1.914	1.634	3.164	1.748	19.579	11.007	1.491	125.153
	(2.728)	(1.334)	(1.157)	(3.248)	(2.618)	(1.241)	(1.164)	(0.000)	(1.175)	(1.113)	(1.271)	(1.140)	(1.083)	(0.048)	(0.114)	(9.346)
Log Family Income AE																
c1*age = 26*	5.812	18.777	2.592	5.741	6.613	7.630	13.493	0.582	1.030	2.537	1.266	2.697	1.684	10.279	0.461	70.454
	(1.961)	(1.527)	(0.905)	(1.113)	(1.207)	(1.255)	(1.026)	(0.596)	(0.900)	(0.959)	(0.890)	(0.896)	(0.611)	(0.019)	(0.016)	(7.394)
age = 30	11.740	13.943	0.611	12.080	10.232	10.231	9.327	1.025	0.773	1.563	2.315	2.166	2.320	10.348	0.577	78.327
	(1.689)	(1.284)	(0.918)	(1.585)	(1.496)	(1.005)	(0.982)	(0.570)	(0.958)	(0.954)	(0.938)	(0.964)	(0.451)	(0.020)	(0.019)	(7.081)
age = 35	13.890	12.723	0.484	15.853	10.260	9.670	8.114	0.258	1.316	2.642	2.437	2.082	3.307	10.385	0.649	83.036
	(1.872)	(1.286)	(0.962)	(1.659)	(1.636)	(1.145)	(1.113)	(0.608)	(0.996)	(0.996)	(1.015)	(1.047)	(0.328)	(0.021)	(0.023)	(7.910)
age = 40	17.781	11.570	2.313	18.747	11.635	10.184	8.015	0.513	2.479	3.401	3.083	3.088	3.847	10.461	0.697	96.657
	(1.999)	(1.289)	(1.036)	(1.752)	(1.824)	(1.247)	(1.061)	(0.647)	(1.062)	(1.056)	(1.056)	(1.111)	(0.322)	(0.022)	(0.026)	(8.170)
age = 45	17.785	10.299	0.059	20.728	10.744	8.868	6.462	0.449	0.810	2.552	3.311	2.760	4.967	10.564	0.716	89.794
	(2.091)	(1.231)	(1.040)	(1.954)	(1.948)	(1.196)	(1.086)	(0.789)	(1.031)	(1.090)	(1.076)	(1.046)	(0.492)	(0.024)	(0.031)	(8.029)
age = 50	21.351	9.566	1.723	22.849	11.988	9.393	7.378	3.396	2.722	3.672	4.401	3.942	6.297	10.651	0.757	108.677
	(2.173)	(1.363)	(1.086)	(2.156)	(2.049)	(1.250)	(1.069)	(1.159)	(1.066)	(1.076)	(1.148)	(1.092)	(0.783)	(0.031)	(0.043)	(8.565)

Table E.12: Percent Contributions to Variance of Outcomes at Various Ages - Women Born 1964–1974

	(1) Educ	(2) μ	(3) η	(4) ν	(5) Emp	(6) ω	(7) Hours	(8) Unearn Inc	(9) ϵ^{ED_s}	(10) $\tilde{\mu}_s$	(11) η^s, ν^s	(12) ω_s	(13) Mar Hist	(14) Mean	(15) Var	(16) *Sum*
Log Earnings																
c1*age = 26*	12.091	9.256	2.052	8.666	25.238	4.254	12.953	0.000	0.036	-0.556	-0.287	-0.175	3.537	9.609	1.404	77.066
	(2.515)	(1.107)	(0.716)	(1.117)	(1.306)	(0.760)	(1.077)	(0.000)	(0.670)	(0.656)	(0.662)	(0.651)	(0.933)	(0.041)	(0.055)	(5.446)
age = 30	5.207	6.402	1.213	20.303	27.642	5.023	9.287	0.000	-0.826	-0.973	-0.260	-0.031	4.181	9.620	1.773	77.168
	(1.070)	(0.877)	(0.680)	(1.451)	(1.081)	(0.741)	(0.809)	(0.000)	(0.673)	(0.654)	(0.653)	(0.640)	(0.622)	(0.037)	(0.046)	(5.344)
age = 35	5.775	6.422	2.042	24.710	29.060	5.011	8.288	0.000	0.307	-0.364	-0.381	0.245	3.099	9.673	1.952	84.215
	(0.973)	(0.838)	(0.643)	(1.571)	(1.044)	(0.761)	(0.739)	(0.000)	(0.616)	(0.596)	(0.608)	(0.607)	(0.494)	(0.038)	(0.050)	(5.066)
age = 40	6.015	7.006	1.660	28.950	30.710	5.048	8.282	0.000	-0.182	-0.418	0.311	0.730	0.956	9.789	1.994	89.070
	(1.031)	(0.857)	(0.720)	(1.652)	(1.116)	(0.824)	(0.753)	(0.000)	(0.650)	(0.643)	(0.628)	(0.617)	(0.328)	(0.039)	(0.054)	(5.324)
age = 45	6.603	5.333	1.120	31.959	32.241	4.804	6.824	0.000	-0.578	-0.974	-0.687	-0.355	0.172	9.894	2.040	86.463
	(1.198)	(0.859)	(0.722)	(1.853)	(1.204)	(0.878)	(0.838)	(0.000)	(0.702)	(0.700)	(0.666)	(0.625)	(0.194)	(0.043)	(0.067)	(5.683)
age = 50	7.085	5.845	0.434	30.241	32.710	4.244	6.151	0.000	-0.310	-0.908	0.433	-0.483	0.673	9.878	2.188	86.115
	(1.315)	(0.880)	(0.645)	(2.375)	(1.337)	(0.831)	(0.838)	(0.000)	(0.633)	(0.642)	(0.633)	(0.635)	(0.401)	(0.058)	(0.104)	(5.712)
Log Family Earnings																
c1*age = 26*	7.063	9.625	2.872	8.286	10.458	3.526	11.121	0.000	0.717	4.868	1.345	4.904	30.595	10.555	0.962	95.381
	(2.944)	(1.277)	(0.961)	(1.089)	(1.043)	(1.119)	(1.174)	(0.000)	(0.945)	(1.053)	(0.964)	(0.996)	(1.334)	(0.031)	(0.056)	(7.730)
age = 30	12.733	7.993	1.196	17.693	11.858	4.367	8.287	0.000	2.803	4.656	4.029	4.275	26.532	10.753	1.075	106.424
	(1.772)	(1.218)	(1.062)	(1.433)	(1.174)	(1.127)	(1.141)	(0.000)	(1.173)	(1.095)	(1.109)	(1.118)	(1.083)	(0.023)	(0.045)	(8.155)
age = 35	14.092	6.387	1.650	19.334	10.440	4.106	6.617	0.000	4.114	4.593	2.978	4.328	26.531	10.902	1.179	105.169
	(2.022)	(1.160)	(1.078)	(1.551)	(1.170)	(1.150)	(1.103)	(0.000)	(1.162)	(1.136)	(1.202)	(1.111)	(1.119)	(0.025)	(0.049)	(8.083)
age = 40	17.252	7.780	2.958	21.515	12.388	5.071	7.698	0.000	5.625	4.904	5.126	4.909	27.266	10.968	1.312	122.492
	(2.150)	(1.176)	(1.129)	(1.595)	(1.185)	(1.151)	(1.118)	(0.000)	(1.180)	(1.107)	(1.236)	(1.111)	(1.171)	(0.029)	(0.058)	(8.331)
age = 45	17.837	6.245	2.018	24.513	13.546	4.897	6.599	0.000	5.605	3.745	4.589	4.731	27.963	10.968	1.490	122.288
	(2.154)	(1.182)	(1.129)	(1.858)	(1.269)	(1.111)	(1.055)	(0.000)	(1.188)	(1.160)	(1.178)	(1.077)	(1.287)	(0.035)	(0.072)	(8.332)
age = 50	15.494	6.109	1.703	22.842	13.490	3.019	5.606	0.000	5.303	2.936	5.342	2.761	29.628	10.857	1.784	114.235
	(2.190)	(1.121)	(1.015)	(2.564)	(1.415)	(1.013)	(1.032)	(0.000)	(1.126)	(1.062)	(1.090)	(1.025)	(1.866)	(0.048)	(0.117)	(8.090)
Log Family Income AE																
c1*age = 26*	10.837	11.527	2.055	3.768	-0.148	3.665	10.268	0.029	0.955	3.982	1.010	4.894	6.457	10.155	0.603	59.300
	(2.000)	(1.223)	(0.837)	(0.836)	(1.099)	(1.052)	(0.973)	(0.655)	(0.821)	(0.941)	(0.850)	(0.892)	(0.986)	(0.024)	(0.023)	(6.767)
age = 30	12.741	9.469	1.637	8.548	1.233	5.302	7.938	1.884	2.895	5.909	4.478	6.517	5.925	10.231	0.662	74.477
	(1.471)	(1.077)	(0.884)	(0.990)	(0.985)	(0.983)	(0.920)	(0.622)	(0.917)	(0.911)	(0.929)	(0.929)	(0.604)	(0.022)	(0.017)	(6.875)
age = 35	11.843	8.124	1.419	9.188	1.208	5.687	6.905	3.186	3.367	6.395	4.565	6.853	7.278	10.294	0.672	76.018
	(1.513)	(1.055)	(0.864)	(1.028)	(1.006)	(1.002)	(0.898)	(0.657)	(0.907)	(0.998)	(1.009)	(0.937)	(0.626)	(0.022)	(0.018)	(6.992)
age = 40	12.550	9.343	1.976	10.721	1.455	6.017	7.822	3.376	4.771	6.518	5.803	6.027	8.797	10.407	0.683	85.176
	(1.588)	(1.106)	(0.922)	(1.058)	(1.083)	(0.977)	(0.918)	(0.672)	(0.927)	(0.976)	(1.001)	(0.980)	(0.740)	(0.022)	(0.020)	(7.232)
age = 45	13.147	9.710	2.574	14.827	2.822	6.323	7.733	3.349	5.730	5.991	5.615	6.390	10.750	10.547	0.724	94.960
	(1.720)	(1.186)	(0.995)	(1.301)	(1.177)	(1.109)	(0.932)	(0.713)	(1.027)	(1.082)	(1.063)	(1.012)	(0.985)	(0.023)	(0.025)	(7.992)
age = 50	14.194	9.037	1.466	15.693	4.131	5.745	7.322	3.781	5.164	4.027	5.869	4.574	14.161	10.615	0.830	95.162
	(1.846)	(1.195)	(0.975)	(1.831)	(1.352)	(1.126)	(1.049)	(0.948)	(1.084)	(1.063)	(1.039)	(1.081)	(1.554)	(0.031)	(0.044)	(7.862)

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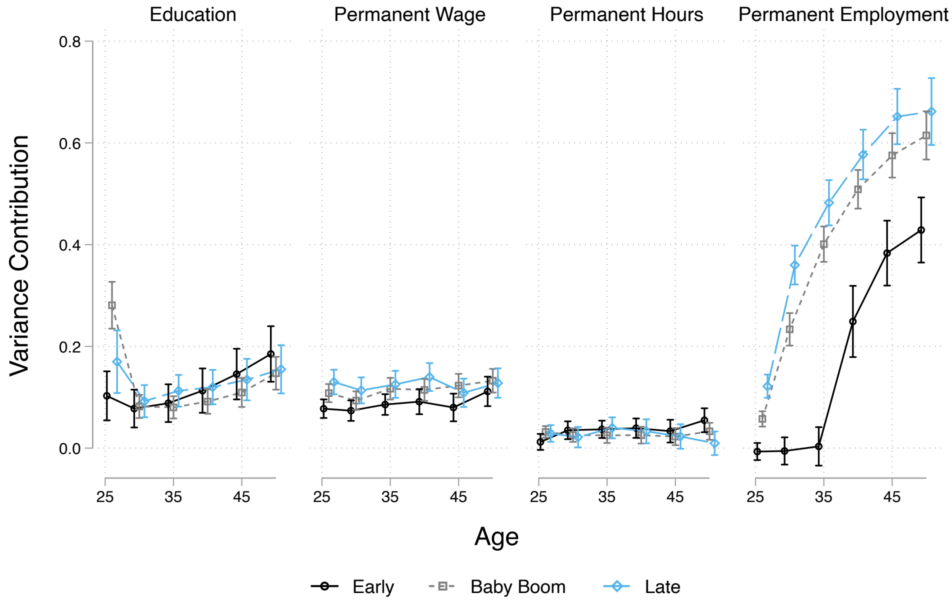
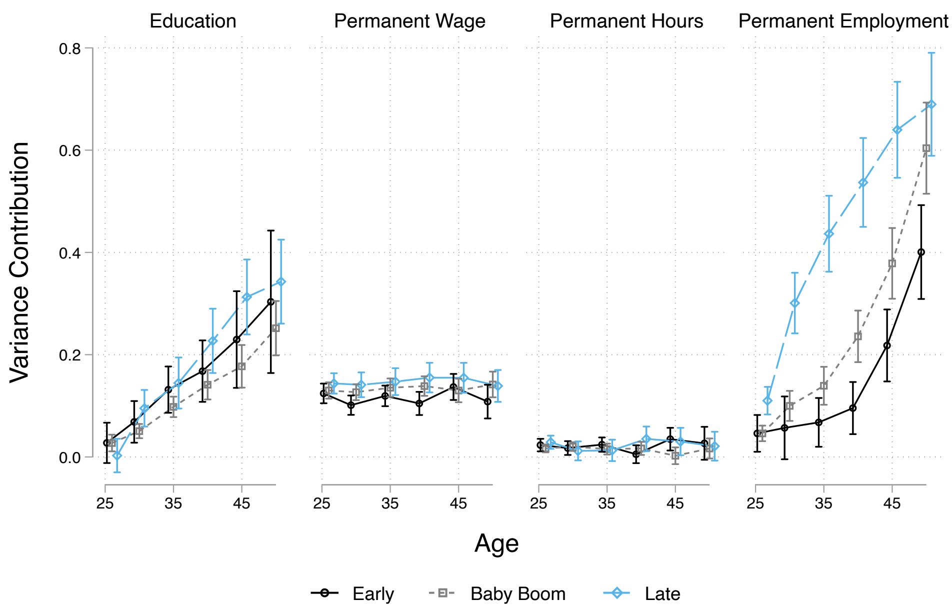
Figure E.1 Contributions to Earnings Variance by Cohort: Permanent Characteristics

Panel A: Women



Panel B: Men



This figure displays, by cohort, the contribution of different model components to variance in earnings at ages 26, 30, 35, 40, 45, and 50. See the introduction to Section 5 and Section 5.1 for a description of the components and the variance decomposition methodology, respectively. Early, baby boom, and late cohorts correspond to birth years 1935–1944, 1945–1962, and 1964–1974, respectively. 90% confidence intervals are calculated using 500 bootstrap samples.