Earnings, Marriage, and Lifetime Family Income: Generational Change for Men and Women*

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Abstract

We study generational change in the role of labor market behavior and marriage in determining the family income that individuals experience over their adult lives. Building on Altonji, Giraldo-Páez, Hynsjö, and Vidangos (2022), we estimate a model of individual earnings, marriage, divorce, fertility, and nonlabor income, where key parameters vary with birth year. For the 1935–44, 1945–62, and 1967–80 birth cohorts, we use the model to measure the dynamic responses of earnings, marital status, and family income to various labor market shocks, education differences, and permanent wage heterogeneity. For each cohort, we also provide gender-specific estimates of the contribution of education, permanent wages, labor market shocks, spouse characteristics, spouse wage shocks, and marital histories to the variance of lifetime family income. For both the dynamic responses and the variance decompositions, we isolate the importance of effects on marriage probabilities and on spouse characteristics (sorting). We find that gender asymmetries are substantially smaller for more recent cohorts. The decline reflects the increase in the labor supply of married women as well as other changes. We also find that own characteristics have become increasingly important in the determination of lifetime family income for women, while variation in spouse characteristics has become less important. The opposite is true for men. Gender differences in the sources of inequality in lifetime family income have narrowed.

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1 Introduction

The dynamics and distribution of family income during adulthood play a central role in the determination of well-being. To understand family income, one must model not only the determinants of own earnings, but also the determinants of marriage, of whom a person marries, and of a spouse's earnings. For example, an unemployment shock affects future income by altering the path of own work hours, wage rates, and, thus, own earnings. But it can also influence one's family income by affecting the probability of finding a spouse and the characteristics of that spouse. A divorce shock not only influences own labor supply and wage rates but it also has an obvious effect on access to a spouse's earnings and it may additionally affect nonlabor income.

Furthermore, it is not just the dynamics of family income that depend on marriage transitions and the income processes of partners. These processes also shape the distribution of income that a person experiences as an adult. Of course, individual-specific factors affect a person's lifetime family income through own earnings. These include education and the permanent components that influence wage rates, employment, and work hours. They also include wage, employment, and hours shocks. But these factors also contribute to inequality in lifetime resources by influencing an individual's marital history and well as whom that person marries. Randomness in whom one marries also contributes to variation in individuals' family income. It also follows that gender differences in the processes that drive earnings while single and while married will lead to gender differences in family income fluctuations. For example, if women work much less than men while married, then own wage and unemployment shocks will be less important for women, while marital sorting will be more important.

Altonji, Giraldo-Paez, Hynsjö, and Vidangos (2022; henceforth AGHV) use a statistical model of earnings, marriage, marital sorting, fertility, and nonlabor income to study how shocks and permanent differences across individuals affect future earnings and family income. AGHV also use the model to decompose the variance in lifetime family income between the ages of 25 and 55. The equations of the model depend upon gender, and they find large differences between men and women in the impulse response of work hours, wages, earnings, and family income per adult equivalent to marriage and divorce shocks as well as to labor market shocks. They also find that marital sorting on education and wages plays a much stronger role for women than for men in the evolution of family income and in the variance of family income during adulthood. These results are driven by the fact that women work much less than men while married, earn lower wage rates, and account for only about 30% of the family earnings of married couples. Consequently, shocks affecting the wage rates and employment status of men are more consequential for family income than shocks affecting women, while the return to education and the permanent component of wages operates through spouses to a much greater degree for women.

AGHV estimate their model using data from the Panel Study of Income Dynamics (PSID) from 1969 to 1996, but for the most part they do not allow the parameters of the equations of their model to shift with birth cohort.[1] As Goldin (2006, 2021), Lundberg and Pollak (2007), Ruggles (2015), Blau and Winkler (2017) and many others have documented, the labor market behavior and fertility of women changed dramatically over the 20th century. Female labor force attachment increased, especially among married women, while rates for men have fallen to some degree. Female education levels rose dramatically relative to men, and the gender gap in wage levels narrowed. The female share of family earnings among married couples has also risen substantially. At the same time, marriage and fertility rates have fallen, meaning that the gender differences in the labor market behavior *within* marriage matter less for income over a lifetime than they did earlier.[2] The upshot is that the economic roles of men and women have converged to some extent, although large differences remain.

What are the implications of these changes for family income? AGHV's analysis suggests that the growing market participation of married as well as single women and the decline in marriage and fertility should change the dynamics of own earnings, family income, and the distribution of family income. In particular, they should reduce gender differences.

In this paper, we study generational change in family income dynamics and distribution, building upon AGHV's model and methodology. To do so, we make two key changes. The first is to extend the PSID sample used through 2019. The extension is essential for studying cohort differences. But this seemingly small change raises many complications, because the PSID switched to every-other-year interviewing after 1997. We make use of the biennial observations, as well as questions about earnings, work hours, and other variables that refer to the calendar year two years prior to the interview. As we explain below, using the data over the entire period requires a number of changes to the model, the estimation procedure, and the choice of employment status measure.

The second change is to allow intercepts and some slope parameters in key equations to vary with birth cohort. In most cases, we do this in a continuous way, using linear, quadratic, or cubic main effects and interactions between cohort and other variables. We estimate the model using the full sample, and then use it to study three broad birth cohorts. The first

[1] They do allow the gender-specific distributions of education to vary across broad birth cohort groups, and their equations for initial conditions at age 25 contain time trends that will capture cohort differences. Many equations also include year polynomials.

[2] Appendix Figures C.1-C.10 display many of these trends using data from the PSID, which is also the data set for this paper's analysis.

is the pre-baby boom cohort: 1935 to 1944. The second is the baby boom cohort, which we define as 1945 to 1962. The third is a post-baby boom cohort: 1967-1980.

Using model simulations, we study the dynamic response of the labor market variables, own earnings, family earnings, family income per adult equivalent, and marital status to a variety of shocks. These include unemployment shocks, wage shocks, divorce shocks, and fertility shocks. We also measure the degree to which the dynamic responses depend upon sorting in the marriage market, which we refer to as the sorting channel, and upon effects on marriage and divorce, which we refer to as the marriage channel.

We find large changes across cohorts in the effects of divorce on the path of earnings. Following a divorce, log earnings for women in the 1935-44 cohort rise by 0.73 and remain elevated for many years. For the 1945–62 cohort, the positive effect peaks at 0.31, while for the 1967–80 cohort the increase peaks at only 0.2 and is close to zero 10 years after the divorce. The change reflects the fact that young married women in the later cohorts worked much more than their counterparts in the earlier cohort. In contrast, for men divorce leads to a small drop in earnings that increases by about 0.05 between the pre-baby boom and post-baby boom cohorts. Consequently, the gender asymmetry in the earnings response to divorce has declined substantially.

We find a large gender asymmetry in the effects of divorce on family earnings and on family income per adult equivalent that has also declined substantially across cohorts. In the 1935–44 cohort, a divorce led to an average decline in family income per adult equivalent of -0.74 followed by a slow recovery to -0.15. The value for the 1967–80 cohort is -0.69. For men, a divorce led to a small *increase* of 0.08 in family income per adult equivalent in the pre-baby boom cohort but a drop of -0.18 for the 1967–80 cohort. Thus the gender differential has dropped from 0.82 to 0.51. The change reflects the growing importance of women's earnings for married couples. When we shut down the marriage channel in our model by eliminating the effects of all variables except age, birth cohort, and calendar time, the negative effect of a divorce on family income per adult equivalent declines, because a future divorce becomes more likely. This reduces the cost to women of an endogenous divorce today. Sorting does not play much of a role in the losses from an exogenous divorce.

The negative effect of an unemployment shock on earnings of married women is -0.08 for the 1935–44 cohort, and fully recovers in 5 years. It more than triples for the 1967-80 cohort, to -0.27. The growth in the earnings response is mirrored in an increase of the responses of family earnings and family income per adult equivalent. The negative effect of unemployment shocks on the path of earnings of married men is -0.26 for the 1935–44 cohort and -0.46 for the most recent cohort. However, the increase in the magnitude of the effect on family income is only 0.08 despite the large growth in the earnings effect. This again reflects the growing importance of wives' earnings for family income. The effect of a wage shock on family income is also much stronger for men than for women in the 1935–44 cohort, and the gap declines substantially across cohorts.

Turning to fertility shocks, we find that the negative effects of a birth to a married woman on family earnings and family income per adult equivalent are relatively stable across cohorts, even though the effect of the birth on own earnings is less negative in the more recent cohort. This change also reflects the increased share of wives' earnings in family income. For single women, in the 1935–44 cohort family earnings fall initially after the birth but then turn positive. The increase reflects the fact that a birth increases the probability of being married by about 30 points for both single men and single women. In contrast, the negative effect of the birth for single women in the 1967-80 cohort is -0.18 in the five years after the birth. The drop in family earnings and family income per adult equivalent is much closer to the drop in earnings. This is because the effect of a birth on marriage for single women in the later cohort declines to only 0.05 one year after the birth and peaks at only 0.10 after six years. These results illustrate the interdependence of changes in labor market behavior and marriage behavior in determining the effects of shocks.

Our second set of results concerns the gender- and cohort-specific effects of education and the permanent component of wage rates on hours, wages, log earnings and log family income per adult equivalent between ages 25 and 55. Like AGHV, we find that the college-high school differential in earnings and family income per adult equivalent is large for both men and women, and that the contribution of marital sorting to the educational gap in family income is much larger for women. However, we also find important changes across cohorts. First, for women the effect of the education differential on family income per adult equivalent grew relative to the differential in own earnings. Second, the contribution of marital sorting to the education differential declines by a small amount across cohorts, as women marry less and work more. Third, for men the educational gap in earnings increases substantially across cohorts, primarily because of an increased education gap in hours prior to age 50. This led to an increase in the effect of education on family income per adult equivalent for men across cohorts. Across generations, the contribution of the marriage channel and the sorting channel to the education differential grows in importance for men relative to women.

We find that the effect of a one-standard-deviation increase in the permanent wage component on female adult earnings grows from an average (across ages) of 0.24 for the 1935-44 cohort to 0.33 for the 1967-80 cohort. The effect on family income per adult equivalent increases from 0.18 to 0.25, a larger percentage increase. The sorting channel accounts for about 31% of this effect in the 1935-44 cohort and 20% for the 1967-80 cohort. High-wage men earn about 0.34 more than average-wage men in the early cohort, which is much larger than the effect for women. However, the size of the increase across cohorts is smaller. The contribution of sorting is smaller than it is for women.

Finally, we use the model to assess the sources of inequality during adult life. Our contribution relative to AGHV is to study generational change. Specifically, we provide gender- and cohort-specific variance decompositions of the variance in the annual average of the log of family income per adult equivalent between ages 25 and 55. The variance components consist of education, fixed unobserved heterogeneity in wages, employment, and hours, employment shocks, hours shocks, wage shocks, random variation in marriage partner characteristics, partner wage shocks, and random variation in marital status over a lifetime.[3]

First, we find that education plays a key role for both men and women and for all cohort groups. The difference between men and women in the role of own education has narrowed across cohorts. For the 1935–44 cohort, the variance contribution was 38.1% for men versus 33.3% for women, whereas for the 1967–80 cohort, the contribution of education is very similar (31.1% for men and 30.1% for women). These contributions capture all of the channels through which education affects lifetime family income in the model, not just own earnings.

Second, the permanent wage component plays a larger role for men than for women. For women, the variance contribution of the permanent wage component rose from 14.5% for the 1935–44 cohort to 20.6% for the 1967–80 cohort. For men, the values are 26.6% and 23.2%. Thus, the difference between men and women in the variance contribution of the wage component has narrowed over time to an even greater extent than for education. The relative increase in the contribution of the permanent wage for women reflects at least in part the increased participation of women in the labor force and the corresponding larger contribution of women's earnings to overall family income in more recent cohorts.

Third, the combined contribution of the permanent employment component and hours conditional on employment has grown. For women, the contribution rose from 6.6% for the 1935–44 cohort to 17.9% in the later cohort. For men, the increase is from 8.9% to 27.2%. We constrain the variance parameters to be constant across cohorts, so the increase for women likely results from their increased participation in the labor force and the larger share of family income that women's earnings comprise for more recent generations. For men, the increase likely stems from the increased *nonparticipation* of men in the labor force, which increases the sensitivity of employment to the permanent employment component.[4]

Fourth, the contributions of the shocks to wages, hours, and employment are all relatively

[3]The family income distribution also depends on spousal employment and hours shocks, fertility shocks, and nonlinearities and interactions, which we lump into a separate category.

[4]We obtain smaller variance contributions when we use alternative estimates of the variance of the employment component, but the gender differences and large changes across cohorts remain.

small, in large part because effects of the shocks are sufficiently transitory that they fade over the course of a lifetime.

Fifth, random variation in marital histories (conditional on permanent characteristics) accounts for about 5% of the variance in family income per adult equivalent, with no clear cohort trend. For men, the contribution has fallen somewhat, from 5.25% for the 1935–44 cohort to 2.55% for the 1967–80 cohort. Overall, variation in marital histories matters a little more for women than for men.

Sixth, we find substantial gender convergence in the importance of random variation in whom one marries. For women, the combined variance contributions of random variation in spouse's education, the spouse's permanent wage component, the spouse's autoregressive wage component and the permanent employment and hours components declined from 25.8% for the 1935–44 cohort to 20.2% for the 1967–80 cohort. For men, the corresponding values are 9.2% and 13.1%, indicating growth in the importance of randomness in matching, but from a lower starting point.

Seventh, we find that the contribution of sorting on education and the permanent and transitory wage components to the variance of lifetime income fell. The combined contribution decreased from 17.9% for women in the 1935–44 cohort to 12.9% for those in the 1967–80 cohort. The corresponding values for men are 12.5% and 10.3%.

Overall, the variance decompositions suggest that as gender roles have changed, with women's labor force participation increasing (along with marriage and fertility rates falling), own characteristics have become increasingly important in the determination of lifetime family income for women in more recent cohorts, while variation in spouse characteristics has become less important. This has contributed to a narrowing of gender differences in the sources of variation in family income.

Our paper, like AGHV, builds on several literatures. We already mentioned the vast literature on long-term changes in female labor supply, wages, fertility, and marriage. Our paper also relates to the extensive literature on marriage, divorce, and marital sorting. Browning, Chiappori, and Weiss (2014) survey the literature on marriage and divorce in an environment where search costs are relatively low.[5] This literature explores the implications of comparative advantage within the family and of competition in the marriage market for who gets married, and who marries whom. A large literature considers assortative matching and marriage when search costs are substantial.

Especially relevant to our research are papers such as Fernandez and Rogerson (2001),

[5]This literature includes the seminal contributions of Becker (1973, 1974) and subsequent papers such as Becker, Landes, and Michael (1977), Weiss and Willis (1993), Choo and Siow (2006), Chiappori and Oreficce (2008), and Chiappori, Iyigun, and Weiss (2009).

Fernandez, Guner, and Knowles (2005), Hryshko, Juhn, and McCue (2017), Eika, Mogstad, and Zafar (2019), and Chiappori et al. (2020), who study the connection between trends in assortative mating and trends in inequality. Heathcoate, Storesletten, and Violante (2010) use a two-person household model with assortative mating fixed and show that changes in the wage structure and dynamics can explain changes in the cross-sectional distributions of individual hours worked, household earnings, and household consumption. We consider sorting on *all* of the variables that matter (in our model) for future earnings and nonlabor income, and also allow assortative mating to change over time. We quantify cohort differences for men and women in the importance of the sorting channel and the marriage channel in shaping the influence of education and the permanent wage component on the distribution of lifetime family income.

Finally, our work also 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) and Heim (2007), who study change over time. Juhn and McCue (2016) consider the marriage gap in earnings for women. The large literature on the effects of children on employment, hours, and wages includes recent papers by Kleven et al (2019) and Kuziemko et al (2018). 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.[6] The equations of our earnings model draw on this vast literature, and our contribution, building on AGHV, is to pull together the components into a dynamic model of lifetime earnings and family income for both men and women that can be used to study generational change.

Our paper also builds on prior work that investigates multivariate processes for earnings, with equations for employment, hours, wage rates, and, in some cases, job mobility.[7] [8]

[6]See Jacobson, Lalonde, and Sullivan (1993), Davis and von Wachter (2011), and Altonji, Smith, and Vidangos (2013), among others.

[7]Multivariate models of earnings dynamics include Abowd and Card (1987, 1989), Low, Meghir, and Pistaferri (2010), Altonji, Smith, and Vidangos (2013), and Card and Hyslop (2021). A number of recent papers do not focus on earnings but provide structural models of wage rates, job mobility, and employment dynamics. These include Barlevy (2008) and Bagger et al (2014) among others. Our model is most closely related to Altonji, Smith, and Vidangos (2013). They focus exclusively on the earnings process of male heads of household and consider job mobility. A separate literature estimates univariate processes for earnings and/or family income, often with a focus on implications for inequality at various ages or over the lifecycle. Recent contributions include DeBacker et al. (2013), Karahan and Ozkan (2013), Blundell, Graber, and Mogstad (2016), Arellano, Blundell, and Bonhomme (2017), Guvenen et al (2021), and Hu, Moffitt, and Sasaki (2019). See Altonji, Hynsjo, and Vidangos (2022) for a brief overview of the multivariate and univariate literatures, with detailed references.

[8]Our work is also relevant for a recent literature in macroeconomics that has begun to account for gender

The remainder of the paper is organized as follows. Section 2 discusses the data. Section 3 discusses the model and selectively discusses the estimates, with additional details relegated to Appendix B. Section 4 discusses the fit of the model. In section 5, we present impulse response functions which trace the responses of key variables to exogenous shocks and consider the role of marital sorting and marriage formation in those responses. Section 6 considers the effects of education and the permanent wage component on family income over the lifecycle. Section 7 reports decompositions of the variance of outcomes over the lifecycle into several sources. Section 8 concludes.

2 Data

We mainly followed the sample selection and variable construction of AGHV, extending the dataset to study the 1969-2019 waves of the PSID. (AGHV use the 1969-1997 waves.) The main challenge to extending the data past 1997 was that the PSID switched to a biennial interview schedule after that year. To accommodate the changes in the availability of annual information for key variables, we either changed the survey questions that informed some of the variables to ensure comparability across the 1997 change or used new questions to supplement for missing data. For example, we now use two-year retrospective questions for some variables. Here we highlight some of the key differences in the variable construction. Appendix A contains detailed, complete information on the data.

First, we made use of questions about weeks worked, hours worked, and earnings that refer to two years prior to the survey in addition to the questions about the calendar year prior to the survey. Second, we used annual earnings divided by annual hours as our primary wage measure, rather than the wage rate for the job held at the survey date because the latter is not available in non-survey years.

Third, the mutually exclusive labor force status measures refer to the calendar year rather than the survey date. Not working (N) is 1 if the person did not work positive hours in the year and 0 otherwise. Unemployment (U) is 1 if the person worked positive hours during the year ($N = 0$) and reported positive weeks of unemployment. Employed (E) is 1 if $N = 0$ and the person reported no weeks of unemployment. Note that the small set of person-year observations of individuals who experience unemployment but work zero hours are classified as out of the labor force rather than unemployed. We denote participation as P, where $P = E + U$. Because wives were not asked whether they had any hours of unemployment

differences and the role of the family in studying aggregate fluctuations, including, for example, Mankart and Oikonomou (2017), Albanesi (2020), and Fukui, Nakamura, and Steinsson (2020). See also Doepke and Tertilt (2016) and Borella, De Nardi, and Yang (2018). We focus on idiosyncratic rather than aggregate risk.

in the previous year prior to the 1975 survey, all of our fit graphs and impulse response functions exclude ages 25-30 for women in the 1935–1944 birth cohort.

Fourth, nonlabor income NLY_{it} is constructed in the same way as in AGHV: it is household taxable income plus transfers received minus earned income. However, the PSID does not ask a two-year retrospective question about taxable income or transfers, so we do not have this measure for odd years after 1997. For this reason, we modeled nonlabor income as depending on contemporaneous variables and an autoregressive error process, the latter of which we estimated only using data prior to 1997.

Fifth, for the even years after 1997, we imputed data for marital status and number of children. For children, we use the Childbirth and Adoption file to obtain data for age and number of children at all years for the sample members. For marriage, we used a variety of methods to impute even-year marital status. The simplest case for imputation was when the sample member's marital status and spouse were the same in two adjacent odd years. When the marital status changed across odd years, we utilized the move-in/move-out data to impute the year of marital status change to mirror the construction of the PSID's own inclusive-of-cohabitation marriage variable. For all remaining cases of missing marital status, we used the Marital History file to impute marital status when possible.

In making decisions about data construction, we compared means, year-to-year changes, and dynamics to values prior to 1997, when the PSID was an annual survey. For the most part, the measures match up fairly well. However, we cannot rule out that differences in the data play some role in differences in dynamics.

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

Our econometric model is very similar to that in AGHV, which provides a more detailed discussion. The main difference is that in a number of equations we add gender-specific controls for birth cohort and allow for interactions between birth cohort and some of the other variables. Because of the similarities, 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.

The model has six parts. The first specifies the joint distribution of employment status, marital status, and number of children at age 25 conditional on education, gender and cohort. The second part is for labor force status, hours, wage rates and earnings. The third is for nonlabor income and the identities for family income and family income per adult equivalent (y_ae) as a function of earnings, spouse's earnings, nonlabor income, and the number of adult equivalents. The fourth part of the model concerns marital status transitions. The fifth part concerns marital sorting. The sixth part determines fertility (after age 25).

The model contains 42 equations and 876 parameters, far too many to allow a full discussion in the text. Instead, we provide a high-level summary of the model, providing details about a few of the equations that play a particularly important role in the impulse response functions and the distribution of earnings and family income. The tables in Appendix B report the parameter estimates for all of the equations, and the table notes provide information about the estimation procedure.

A word about notation. The superscript s on a model parameter indicates that the dependent variable refers to the spouse of the PSID sample member. Similarly, the subscript s on a variable indicates that the variable refers to the spouse of sample member i. To make the main effects of variables that enter as polynomials or are interacted with other variables easier to interpret, in the models we normalize education around 12 years of schooling, calendar year t around 1994, age around 34, and potential experience pe_{it} around 16 (16 = age norm - education norm - 6).

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 combination, 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. The birth cohorts are 1935–1944, 1945–1953, 1954–1962, 1963–1966, 1967–1973, 1974–1980, and 1981–1997.[9] 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.

3.2 Earnings

Similarly to AGHV, the earnings model consists of (1) the initial condition for employment status mentioned above, (2) equations for annual employment status, (3) equations governing the initial value and the evolution of hourly wage rates and (4) an equation for annual work hours conditional on positive hours ($N_{it} = 0$).[10]

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

[10] As in AGHV, we abstract from modeling job mobility and the presence of job-specific wage and hours components.

3.2.1 Log Hourly Wages

We estimate separate models for men and women. The wage measure $wage^{*}_{it}$ is equal to the log hourly wage $wage_{it}$ plus classical measurement error. Given the importance of wage rates for family income, especially the error components, we provide the details here, drawing heavily on AGHV. The log wage is determined by the following equations:

$$
\begin{aligned}
wage_{it} &= E_{it} \cdot wage^{lat}_{it} && (1)\\
wage^{lat}_{it} &= X^{w}_{it}\gamma^{w}_{X} + B^{2}_{i}\gamma^{w}_{B^2} + p(CH_{it}; B, B^{2}_{i})\gamma^{w}_{CH} + LFS_{i,t-1}\gamma^{w}_{LFS} && (2)\\
&\quad + p(Mar_{it}; B, B^{2}_{i})\gamma^{w}_{mar} + \mu_i + \omega_{it} + \varepsilon^{w}_{it} && (3)\\
\omega_{it} &= \gamma^{\omega}_{0} + \rho^{\omega}\omega_{i,t-1} + \gamma^{\omega}_{U}U_{i,t-1} + u^{\omega}_{it} \text{ if } age_{it} > 25 && (4)\\
\omega_{it} &= \omega_{i25} \text{ if } age_{it} = 25\\
\mu_i &= N\left(0, \sigma^{2}_{\mu}\right);\ u^{\omega}_{it} \sim N\left(0, \sigma^{2}_{u^{\omega}}\right);\ \epsilon^{w}_{it} \sim N\left(0, \sigma^{2}_{\epsilon^{w}}\right)
\end{aligned}
$$

Equation (1) says that an employed (i.e. $E_{it} = 1$) individual's $wage_{it}$, equals the "latent wage" $wage^{lat}_{it}$. While not employed, $wage^{lat}_{it}$ captures the process for wage offers. At a given point in time the individual might not have such an offer. The formulation parsimoniously captures the idea that worker skills and worker-specific demand factors evolve during a nonemployment spell.

Equation (2) states that $wage^{lat}_{it}$ depends on a set of regressors. The vector X^{w}_{it} contains a cubic time trend, $EDUC_i$, potential experience PE_{it}, PE^{2}_{it}, PE^{3}_{it}, and the interaction between $EDUC_i$ and both PE_{it} and PE^{2}_{it}. B_i refers the individual's birth year. Vector CH_{it} consists of counts of children aged 0 to 5, 6 to 12, and 13 to 18 and $p(CH_{it}; 1, B_i, B^{2}_{i})$ is the vector consisting of CH_{it} and its interactions with B_i and B^{2}_{i}. Similarly, the vector $p(Mar_{it}; B_i, B^{2}_{i})$ consists of marital status Mar_{it} and its interactions with birth cohort and birth cohort squared. For men, we exclude main effects and interactions involving B_i and CH_{it}. For women, but not men, $wage^{lat}_{it}$ also depends on 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 $p(Mar_{it}; B, B^{2}_{i})$ may be correlated with μ_i, we instrument them using deviations from their i specific means.[11]

The wage also depends on permanent unobserved "ability," μ_i, the stochastic wage component, ω_{it}, and an i.i.d. shock ε^{w}_{it}. We diverge from the model in AGHV with the inclusion of the i.i.d. shock to wages. As a result, we adjusted our estimation strategy. In particular, we estimated the variance of measurement error using the data and allowed it to be

[11] 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_{it-1}, P_{it-2}, P_{it-3}, U_{it-1}, and U_{it-2} estimated using women between ages 23 and 27.

gender-specific. Appendix B.2 provides the details.

Equation (4) states that the unobserved stochastic wage component ω_{it} depends on $\omega_{i,t-1}$, the lag of unemployment $U_{i,t-1}$, and the mean-zero wage shock u^{ω}_{it}. We experimented with including P_{it-1} but found it had little impact.[12] For women, who are more likely to have long spells of nonparticipation, we excluded $U_{i,t-1}$ from (4) because otherwise the model implies too large a penalty from nonparticipation. Instead, we include $LFS_{i,t-1}$ in (2).

Appendix Table B.1a columns 1 and 2 report 2SLS estimates of (2) for men and women, respectively. The marital premium is 0.050 (0.010) for men. For women, the premium is small and negative for the early cohorts but rises slowly with birth cohort. It is essentially 0 for the 1960 cohort and 0.043 for the 1980 cohort. Wages are substantially lower for women with children, and the penalty increases with birth cohort. For women the coefficients on the three lags of participation sum to 0.236, while the lags of unemployment enter negatively.

Appendix Table B.1b reports the parameters for the ω_{it} process as well as the variances of μ_i, ε^w_{it}, and measurement error.[13] For men, the effects of unemployment $U_{i,t-1}$ in (4) are defined relative to lack of unemployment. 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 important. The estimate of σ_μ is 0.350 (0.011) for men and 0.331 (0.013) for women.

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. We include $E_{i,t-1}$ and $U_{i,t-1}$ in the model as well as a normally distributed random effect ν_i. The random effect has a coefficient of 1 in the latent indices for E and U relative to N. 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^2_ν. In simulations, we found the model produced too little persistence in employment, leading to an understatement of employment at older ages. To address this shortcoming, we constrained σ^2_ν to be double the unrestricted MLE estimate. This improved the fit at long lags considerably, although we

[12]We estimate (4) after replacing ω_{it} and $\omega_{i,t-1}$ with the 2SLS residual $\hat{e}^w_{it}$ from (2) and its lag. That residual is the sum of ω_{it} plus μ_i, ε^w_{it} and the measurement error me^*_{it}. Consequently, we use the second and third lags of the first difference of the wage residuals and the deviations of $U_{i,t-1}$ from the mean for i as instrumental variables.

[13]The regression coefficients and variance parameters of (4) are estimated using a combination of 2SLS (to account for endogeneity of and $U_{i,t-1}$, labor market status in the equation for men, measurement error, and for the presence of μ_i) and methods of moments. See AGHV and Appendix Section B.2.

still understate persistence in employment for men.[14]

The multinomial logit coefficients are presented in Appendix Table B.2. Due to space constraints, we do not discuss them in detail. The results indicate that there is strong state dependence and substantial unobserved heterogeneity. For men, marriage increases employment and the coefficients on the child variables CH_{it} are small and statistically insignificant. For women, children under 5 have a large negative effect of employment. Appendix Figures C.1-C.2 graph the cohort-specific profiles of the predicted employment, unemployment, and nonparticipation rates by age and gender, not holding other variables fixed. However, because the cohort range is 10 years for the early cohort, 18 for the baby boom cohort, and 14 for the post baby boom cohort, both cohort and time vary somewhat across ages and contribute to the age profiles. The nonparticipation rate for men does not change much between the pre-baby-boom and baby-boom cohorts, but increases by about 0.03 in the post baby boom cohort. For women, nonparticipation decreases slightly between the pre-baby-boom and baby-boom cohorts and substantially between the baby-boom and post baby-boom cohorts.

3.2.3 Log Annual Hours

The model for $hours^*_{it}$ conditional on labor force participation is reported in Appendix Table B.3a and b. For both men and women, we pool singles and married but include Mar_{it}. We include cubics in pe_{it}, and t, and the quadratic of B_i. The equations include U_{it}, which picks up effects of hours lost to unemployment, and the wage. For women, we include CH_{it}, and allow the effects of most variables to depend on marital status. We also include the spouse variables $wage^{lat}_{st}$ and U_{ist}. Some of the variables are interacted with B_i and B_i^2 and/or with powers of t.

The $hours^*_{it}$ error term is

$$\eta_i + \omega^h_{it} + \varepsilon^h_{it} + me^h_{it}$$

where

$$\omega^h_{it} = \rho^h_{\omega^h}\omega^h_{i,t-1} + u^h_{it}.$$

It depends on the unobserved permanent hours component η_i, the autoregressive component ω^h_{it} with innovation u^h_{it}, the i.i.d. error ε^h_{it}, and the measurement error me^h_{it}. Components ω^h_{it} and ε^h_{it} pick up transitory variation in straight time hours worked, overtime, multiple job holding, and nonemployment conditional on annual unemployment status U_{it}. They capture serially correlated and i.i.d. shifts in both worker preferences and job-specific hours

[14] We follow AGHV and set the variance of the unobserved component to 2 times the unrestricted variances estimates of 1.60 for men and 1.62 for women. We have not experimented with this value.

constraints.

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, $\rho^h_{\omega^h}$, and σ_{ε^h} by the method of moments. See Appendix B.3.

For men the wage elasticity is 0.089 (0.012) for the 1960 birth cohort and increases slowly across birth cohorts. Not surprisingly, annual hours worked have a strong negative link to U_{it}. Conditional on employment status, married men work 0.015 (0.008) more hours than unmarried men.

For women the own wage elasticity is 0.244 (0.016) and the spouse wage elasticity is -0.193 (0.019). Neither varies much across cohorts. Married women increase hours in response to spouse's unemployment. Children, especially young children, have a substantial negative effect on hours worked for both single and married women, even conditional on working positive hours. The effects of children under 6 are much larger for married women. The effect declines by a modest amount across cohorts. The effect of older children is more negative for single women.[15]

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. The values of ρ^h are 0.666 (0.039) for men and 0.722 (0.039) for women. The standard deviations of ε^h_{it} and the shocks to ω^h_{it} are substantial. Results are reported in Appendix Table B.3b.

3.2.4 Log Annual Earnings

Because the wage measure $wage^*_{it}$ is equal to annual earnings divided by hours,

$$earn^*_{it} = wage^*_{it} + hours^*_{it} \text{ if } earn^*_{it} > 0,\ hours^*_{it} > 0. \tag{5}$$

In practice, we set $hours^*_{it}$ to $\ln(200)$ when the level of annual hours is less than 200 (including 0), and we set $wage^*_{it}$ to a minimum of $\ln(6.5)$, which is the 1991 real federal minimum wage in 2012 dollars. Consequently, we set the minimum of $earn^*_{it}$ to $\ln(200) + \ln(6.5) = ln(1300)$, including cases in which reported hours over the year are 0 ($P_{it} = 0$).

[15]Due to space considerations we do not discuss time trend estimates even though the trends contribute to differences in cohorts in family income dynamics and distribution. Unsurprisingly, the trends in hours and employment are much larger for married women.

3.3 Nonlabor Income, Family Income, and Family Income per Adult Equivalent

3.3.1 Nonlabor Income

Log nonlabor (or unearned) income, nly_{it}, is observed only at the household level. We specify separate models for married individuals, single men, and single women at age 25. We also use gender-specific models for each marriage transition status—single to single, single to married, married to married, and married to single. There are a total of 10 equations.[16] AGHV included $nly_{i,t-1}$ in the equations. Because values of nly_{it} are only observed in even years after 1996, we exclude $nly_{i,t-1}$ and instead add an AR(1) error to the models. We estimate the AR coefficients using data through 1996. The estimates are reported in Appendix Tables B.4a and B.4b.

3.3.2 Family Earnings, Family Income, and Family Income per Adult Equivalent

The level of family income is given by the identity[17]

$$Y_{it} = \exp^{earn_{it}} + \exp^{earn_{sit}} + \exp^{nly_{it}} . \tag{6}$$

3.3.3 Adult Equivalents

The equivalence scale used in the model only includes the sample member and spouse (if present) as adults, and children of the sample member who are under 18:

$$AE_{it} = (1 + 0.7MAR_{it}) + 0.5(CH05_{it} + CH612_{it} + CH1318_{it}).$$

This formulation ignores the presence of other adults and assumes that both parents fully support their children. See AGHV Section 3.3.6 for further discussion.[18]

[16] See AGHV Section 3.3.5 for additional discussion. We ignore measurement error in $nly_{i,t-1}$ when estimating the model.

[17] As in AGHV, we ignore income from other household members. This amounts to assuming that they do not contribute to the resources available to the sample member. Measured family income Y^*_{it} is $\exp^{earn^*_{it}} + \exp^{earn^*_{sit}} + \exp^{nly_{it}}$. The level of family earnings $FAMEARN_{it}$ is EARN_{it} if single and $EARN_{it} + EARN_{sit}$ if married.

[18] AGHV also consider the alternative assumption that men live with their children only when married.

The alternative assumption about AE only affects results for y_ae_{it} for males. Not surprisingly, they find that it substantially reduces the material gains from marriage for men.

3.4 Marriage

The marriage model closely follows AGHV, with birth cohort main effects and interactions added. It serves the purpose of analyzing gender and cohort differences in the role of marriage in family income dynamics. As discussed above, the initial conditions for marriage and marriage duration at age 25 depend on education, gender, and birth cohort, and are jointly determined with number of children and labor force status. The rest of the model consists of the equations for transitions from single to married, for the joint distribution of spouse characteristics conditional on $i's$ attributes for marriages that form, and a divorce equation.

3.4.1 Single to Married

After age 25 transitions into marriage depend on $i's$ education, wage, employment status, a quadratic in age, the index $CH\_VAR1_{i,t-1}$ measuring the presence of young children, and a cubic time trend. Coefficients for these variables are gender-specific with the exception of the time trend and $CH\_VAR1_{i,t-1}$. In addition, we include B_i^2 and interactions between B_i, B_i^2 and several of the variables. The probit coefficients are shown in Appendix Table B.5. Space constraints preclude a discussion. As is the case in all of the models, it is hard to isolate the effects of birth cohort from the individual coefficients given that the age and time trend polynomials also pick up cohort effects. The effect of the wage rate and P_{it} are positive and the effect of U_{it} is negative for men, not for women. The effect of children on marriage transitions has declined across cohorts, which is consistent with the increase in single parent households in the US and other countries. Model simulations indicate that transition probabilities into marriage across the age profile declined substantially between the 35–44 and 67–80 cohorts.[19]

3.4.2 Married to Married

Appendix Table B.6 reports estimates of a probit model that determines the marriage continuation probability $Prob\,(MAR_{it} = 1|MAR_{it-1} = 1)$. It is based upon AGHV, but it includes interactions between B_i and several of the variables, as well as B_i^2. The effects of individual characteristics such as age, education, and the wage depend on gender. The model includes a polynomial in marriage duration and the effects of duration depend on both t and B_i. The stability of the marriage depends upon the mismatch between wage rates, ages, and education levels of the man and woman. The model also includes the normally distributed marriage-specific heterogeneity term $\xi_{j(i,t)}$, where j indexes the marriage that i is in at year

[19] AGHV experimented with adding $CH612_{it}$ and $CH1318_{it}$ to the marriage transition equations and found that doing so did not matter much.

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.[20]

The variable $wage^m_{it-1}$ has a small positive effect for men, and P_{it} has a substantial positive effect for men. Neither variable matters for women. We have little evidence that the effects of these variables have changed much across cohorts. Both husband's and wife's education increase marital stability. A number of the cohort interaction terms are statistically significant. Model simulations indicate that the age profiles of the male and female marriage continuation probabilities shifted down by a small amount between the 35-44 and 67-80 cohorts (not shown).

Not surprisingly, the lagged index for young children, $CH\_VAR1_{i,t-1}$, has a large positive effect on the continuation probability. The estimate of σ_ξ is 0.505 (0.099), which is substantially larger than AGHV's estimate.

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. The models of the spouse's initial labor market status and age are discussed in Appendix C of AGHV. Our models of those have largely stayed the same except for some cohort interactions. This paper's 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 $CH05_{it-1}$, $CH612_{it-1}$ and $CH1318_{it-1}$ instead of $CH05_{it}$ and replace the terms involving t with B_i. All equations are gender-specific. We estimate by OLS. The mean squared error of the equations provides age- and gender-specific

[20] To improve our fit of the age profile of marriage-to-marriage transition probabilities for the 1967–80 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 dataset of both the simulated data and the PSID data from the 67–80 cohort. The right-hand side of the model included 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 was from the PSID (instead of a simulated observation). The estimated coefficients on the interactions with the PSID variables (and the PSID intercept) produced the regression index that we added to our model of marriage-to-marriage transition probabilities when simulating the model.

estimates of the variance of $\varepsilon_{it}^{ED_s}$, the random component of spouse's education. We assume $\varepsilon_{it}^{ED_s} \sim N(0, \sigma^2_{ED_s})$. The estimates are reported in Appendix table B.7.

3.5.2 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. We restrict variances for female (male) spouses to be the same as the variances for female (male) sample members.

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

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

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

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

Note that we have restricted the coefficient linking μ_{sfi} and μ_{mi} to equal the coefficient linking ω_{sfit_0} and ω_{mi,t_0-1}. After a marriage starts, ω_{sfit} evolves according to equation (4) (shown earlier) evaluated using the parameter values for females. When we simulate the model, we draw μ_{sfi} from $N(\gamma_{m\mu}^{w_s}\mu_i, Var(\tilde{\mu}_{sfi}))$. We draw ω_{sfit} from $N(\gamma_{m\omega}^{w_s}\omega_{mi,t_0-1}, Var(\tilde{\omega}_{sfit_0}))$. The model for female sample members and male spouses is the same.

We use the method of moments to fit $\gamma_{m\mu}^{\mu_s}$ and $\gamma_{m\omega}^{\omega_s}$ to the covariances of the wage residuals of the sample member and the spouse at various leads and lags during the marriage. See Appendix B.4. All parameters depend on whether $B_i \leq$1962. The estimates are shown in Appendix Table B.11. For women, the estimates of $\gamma_{f\mu}^{\mu_s}$ are 0.385 (0.008) and 0.383 (0.014) for those born before 1962 and those born after, respectively. For men, the corresponding values are 0.300 (0.008) and 0.284 (0.009). Thus, there is strong sorting on the wage components, and the effects are larger for women than for men.

3.6 Fertility after Age 25

The initial conditions for children at age 25 were discussed above. Births after age 25 are determined by gender- and marital status-specific probit models. For unmarried individuals, the explanatory variables are $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, $EDUC_i$, the interactions between $EDUC_i$ and a quadratic in B_i, a cubic in a_{it}, a quadratic in t, and B_i^2. For married individuals we add a quadratic in a_{sit} and t_i^3. We restrict the sample to $a_{it} <= 50$. The probit estimates are shown in Appendix Table B.12

4 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. 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. Due to space constraints, here we provide only a brief summary of the findings, focusing on the model's shortcomings. For more details, see Appendix C and the associated results in Appendix Tables C.1-C.3 and Appendix Figures C.1-C.10.

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 model to the PSID. The model misses tend to be more pronounced at younger ages for individuals in the 1935-44 cohort. The reason is that the PSID has relatively few observations for this cohort early in the life cycle. The rest of this section summarizes the fit for specific groups of variables.

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. We slightly and consistently overestimate women's nonparticipation in the 1945–1962 cohort after age 35. As a result, we slightly and consistently under predict 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 1935–44 cohort, the model understates the log wage for women at young ages. For the 1945–62 cohort, the model slightly underpredicts hours for women at older ages (45–55), though it fits the overall age profile reasonably well.

Earnings. The model fits the age profile of log earnings for men quite well overall. For women, the model slightly over-predicts earnings for all cohorts, but especially the 1935–44 group. As a result of the overprediction, the overall mean of log earnings for women in this cohort is 9.12 in the simulated data but 8.97 in the PSID (the miss is 0.15 log points). For the 1967–80 cohort, the miss in the overall mean of log earnings for women is 0.06 log points.

Marriage. On the whole, the model fits the overall marriage rates (mean and standard deviation) as well as age profiles fairly well for both men and women. For the 1935–44 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 0.84 in the model and 0.88 in the data, and the corresponding means for women are 0.75 and 0.83. For the 1967–80 cohort, the model overpredicts marriage somewhat for women at older ages, but it fits the overall marriage rate for women quite well (0.70 in the simulated data versus 0.69 in the PSID).

Family Income. Overall, the model fits the mean, standard deviation, and age profile of log family income for both men and women reasonably well. For the 1935–44 cohort, the model somewhat underpredicts family income 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 10.94 in the simulated data and 11.03 in the PSID (the fit for this group is much better for y_ae). For men in this cohort group, the overall mean of y_ae is 10.37 in the simulated data and 10.29 in the PSID.

Spouse Variables. The model fits the means and standard deviations of spouses' age and education quite well for all cohort groups. The fit of spouses' labor force status, log wage, log hours, and log earnings (including their age profiles) are all broadly similar to the corresponding fit for sample members.

Regression relationships between husband and wife's age (at the start of the marriage) and between husband and wife's education are also similar in the simulated and actual data, for all cohorts. Regressions of the spouse's log wage on the sample member's log wage match closely between simulated and actual data for the older cohorts, but less so for the younger cohorts. For the 1967-80 cohort, the estimated coefficient is somewhat understated in the simulated data for both men (0.23 versus 0.34 in the PSID data) and women (0.23 versus 0.30 in the PSID).

Dynamic Fit of the Model. We evaluate the dynamic fit of the model by estimating (separately for men and women) separate bivariate regressions of log wage, log hours, employment, log earnings, log unearned income, and log family income against their own values at $t-k$, for $k = 1, 3, 6, 8$. For all cohorts, the model somewhat understates the persistence in earnings for both men and women. For example, for cohorts 1945–62, the model understates the coefficient r^k for men by about 0.08 at the first lag and 0.13 at the 8th lag, and for women by about 0.13 at the first lag and 0.07 at the 8th lag. The miss in earnings persistence is primarily driven by an underpredicted persistence in hours (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.

5 The Response of Earnings and Income to Shocks by Birth Cohort

In this section we present impulse response functions (IRFs) which trace the responses of key variables to exogenous shocks.

5.1 Approach to Estimating Impulse Response Functions

We follow AGHV's approach; this paragraph heavily borrows wording from that paper's description of the IRF method.. The IRFs presented in this section refer to "shocks" imposed on the model at age $a_{it} = 34$ for a particular gender-birth cohort group. For a given group, we first obtain "baseline" paths for each variable by using the estimated model to simulate a large number of lives starting at age 25. Next we perform a counterfactual simulation in which we simulate additional lives for the same gender-birth cohort group through age 33 and, at age 34, we impose a "shock" on a particular subgroup of the gender-birth cohort group (usually by marital status).[21] For example, we impose that all married individuals in the gender-birth cohort group become unemployed, or all singles get married, and so on. After the shock, we continue the counterfactual simulation in accordance with the model from age 35 through age 55. We compare the mean path of the counterfactual simulated lives to the mean path for the subset of the baseline simulated lives who were in the same state at age 33. For example when estimating the IRF for a marriage shock, we compare counterfactual and baseline simulated lives for those individuals who were single at age 33.

We also investigate, as in AGHV, how the marriage transition probabilities (the "marriage channel") and sorting equations ("sorting channel") mediate the impact of the shocks. To do so, we use the simulated data to estimate versions of the marriage transition equations and sorting equations that only depend on a quadratic cohort term and third- or fourth-order polynomials in age and calendar time. By replacing the marital transition and sorting

[21] In all simulations, we take the joint distribution of gender, education, and birth year as given and equal to the baseline PSID sample for the particular birth year cohort group.

equations with these new models, we effectively shut down the effect of personal characteristics (other than age) on marriage and sorting. Having replaced the equations, we proceed to estimate the counterfactual in the same way as before. For a given shock, then, we have three additional counterfactual scenarios on top of the base counterfactual which has both marriage and sorting "on." In the first alternative scenario, we only shut off the marriage channel. In the second, we only shut off the marital sorting channel. Finally, in the third, we shut off both the marriage and sorting channel. For each alternative scenario, we interpret the distance between the base counterfactual and the alternative path as the effect of shutting off that particular channel on the impact of the shock.[22]

A word on the figures in this section. In general, point estimate lines display the the gender-group-cohort's mean in the simulation with the shock minus the same group's mean in the baseline simulation, by age. Point estimate lines are thick, while the corresponding 90% confidence bands are thinner but of the same color and line pattern. We obtained the confidence bands using 500 bootstrap replications of the model and IRF estimation procedure. For the figures analyzing the marriage channel and sorting channel, we exclude confidence bands to reduce clutter.

5.2 The Effects of Divorce and Marriage

5.2.1 The Effect of Divorce

Figure 1 panel A shows the mean response to an exogenous divorce shock imposed on married women at age 34 for the 1935-44 birth cohort. Following a divorce, log earnings ($earn_{it}$) (solid blue line) for women in the 1935-44 cohort rise by 0.73 and remain elevated for many years. The increase reflects a sharp increase in $hours_{it}$ (red, short-dashed line) and a smaller, more gradual increase in $wage_{it}$ (long-dashed green line) peaking at 0.07 three years after the divorce. It also reflects an additional effect of divorce on the probability of working positive hours during the year (P_{it}). Because $hours_{it}$ is set to $ln(200)$ and $earn_{it}$ is set to $ln\,(1300)$ when $P_{it} = 0$, P_{it} has a separate effect on $earn_{it}$.[23] The dynamics of the response are driven by state dependence in the labor force state and dynamic effects operating through wages, re-marriage, and fertility. Note that some of the women in the baseline simulation who are married at age 33 divorce at a later age.

Figure 1-B presents corresponding results for the 1945–62 birth cohorts. They show a striking change across cohorts. The positive effect of divorce on $earn_{it}$ peaks at 0.31, which is less than half the value for the pre-baby boom cohort. The smaller value reflects much

[22] In the next section, we use an analogous simulation strategy to measure the contribution of the marriage and sorting channels to the effects of education and the permanent wage component μ.

[23] Appendix Figure D.1 shows the response of employment to a divorce shock for married men and women

smaller increases in $hours_{it}$ and in the $wage_{it}$ as well as a much smaller increase in E_{it} (see Appendix Figure D.1). In turn, several factors contribute to the smaller effects, but the main one is that young married women in the baby boom cohort worked at higher rates for longer hours than those in the prior cohort. For the 1935–44 cohort, the means of simulated $earn_{it}$, $hours_{it}$, $wage_{it}$, and P_{it} for married women at age 33 are 8.3, 6.1, 2.5, and 0.52. These values rose to 9.2, 6.6, 2.7, 0.75 respectively, for the 1945–62 cohort. One could use the model to decompose these cohort differences further, but they appear to be due to changes in the $hours_{it}$, $wage_{it}$ and P_{it} equations and to differences in marital fertility. In contrast, cross-cohort differences in the labor supply and earnings of single women are more modest.

Figure 1-C presents the divorce IRFs for the 1967–80 cohort. The effect of divorce on $earn_{it}$, $wage_{it}$ and $hours_{it}$ declines compared to the 1945–62 cohort by about one-third; the increase peaks at 0.2 two years after the divorce in the case of earnings and 0.17 in the case of hours. After 10 years the effect is close to zero.

The cohort-specific estimates of the effects of divorce for men are in Figure 1 panels D, E, and F. Keep in mind that the scale of the vertical axis of these graphs differs from the scale for women in Figure 1; this is also true in all other figures. In contrast to the large increases for women, pre-baby boom men experience a drop in earnings by 0.09 after a divorce and by about 0.05 after 10 years. For men, the decline increases across cohorts. For the 67–80 cohort, the earnings decline is 0.16 three years after a divorce and 0.09 fifteen years after a divorce. The cross-cohort change is driven by more negative effects of divorce on hours.

Figure 2 displays the IRFs for the effect of divorce on log family earnings ($famearn_{it}$) (long-dashed khaki line) and log family income per adult equivalent ($y\_ae_{it},$) (short-dashed teal line). There are three main findings. First, divorce has much more negative effects on $famearn_{it}$ and y_ae_{it} for women than men in every cohort. Women in the 35-44 cohort experience a drop in $famearn_{it}$ equal to -1.9 (85%) with a gradual recovery to -0.34 (29%) at age 55. The corresponding values for men are -0.30 and -0.09. The much larger drop for women reflects the fact that earnings of married men account for 85% of average family earnings between the ages of 30 and 33 for the 35–44 cohort.

The gender asymmetry in the loss of $famearn_{it}$ is reflected in the IRFs for y_ae_{it}. Women in the 35-44 cohort experience a large drop in y_ae equal to -.74 followed by a partial recovery to -0.12 at age 55. In contrast, men in the 35-44 cohort experience a small *increase* in y_ae_{it} following a divorce, as the loss of spouse's earnings is outweighed by the reduction in ae_{it} because the spouse is no longer present.

The second finding is that family earnings losses following a divorce have decreased for women and increased for men across cohorts, substantially reducing gender differences. For women, the drop in $famearn_{it}$ is -1.90 (85%) for the 35-44 cohort, -1.56 (79%) for the 45-64 cohort and -1.46 (77%) for the 67-80 cohort. In contrast, for men the decline is -0.30 (26%) for the 35-44 cohort, -0.48 (38%) for the 45-62 cohort and -0.66 (48%) for the 67-80 cohort. Underlying the shift is a drop in the spouse's share of family earnings among women married between age 30 and 33 from 85% for the 35–44 cohort to 66% for the 67-80 cohort.

Third, for women the effect of divorce on y_ae dropped in magnitude from -0.74 for the 35-44 cohort to –0.69 for the 67-80 cohort. In contrast, for men the effect of divorce fell from a 0.08 boost to a -0.18 drop for the 67–80 cohort. Thus the gender differential has declined substantially, although it remains large.[24]

We wish to stress that the specific magnitudes and especially the specific timing of the responses should be viewed with caution. We observe only 2,631 divorces in the estimation sample and only 3,406 transitions into marriage. And, as we discuss in AGHV Appendix section D.3, the dynamic specification of the model is simplified in a number of dimensions. But it is clear that divorce has a large negative and persistent effect on y_ae for women and a growing, negative effect for men.

5.2.2 The Role of the Marriage and Sorting Channels in the Effects of Divorce.

Figure 3 explores the role of the marriage and sorting channels in determining the mean response of y_ae_{it} to a divorce shock. (We exclude confidence interval estimates for readability.) The solid black line, denoted "All Channels", is the same as the IRFs for y_ae_{it} in the corresponding panels of Figure 2. For women in the 35–44 cohort, shutting down the marriage channel (short-dashed, light blue line) reduces the effect of the divorce shock 16 years out (age 50) from -0.13 to –0.08. Note that shutting down the marriage channel eliminates the effects of all variables except own age, cohort, and time on the survival of the marriage, including the effects of marriage duration and the marriage heterogeneity component $\xi_{j(i,t)}$. As AGHV point out, marriages in progress at age 34 are positively selected on both marriage duration and the marriage heterogeneity component $\xi_{j(i,t)}$. Eliminating the effects of these variables on divorce probabilities makes a future divorce more likely. This reduces the costs to women of an exogenous divorce shock today.

The small gap between the black lines and the long-dashed gray lines indicate that shutting down the sorting channel only slightly decreases losses from an exogenous divorce. Differences across cohorts in the role of the sorting and marriage channels are small.

Figure 3 panels D, E, and F show the results for married men. The contributions of both the sorting and marriage channels are very small for the 35–44 cohort but they increase as

[24]Due to space constraints, we do not present or discuss IRFs for the response of nonlabor income to a divorce. It constitutes a small share of family income for most individuals. See AGHV for evidence for the baby boom cohort.

the effects of divorce become more negative for men. The relative contribution of sorting is more important for men.

5.2.3 Entering Marriage

Panels A, B, and C of Appendix Figure D.2a display the cohort-specific dynamic response of $hours_{it}$, $wage_{it}$, and $earn_{it}$ to an exogenous "marriage" shock imposed on all women who are single at age 33. Panels D, E, and F display the responses for men. Roughly speaking, the estimates of the effects of entering marriage are equal and opposite to the effects of divorce. For women, wage rates, hours, and earnings all fall, but the magnitude of these effects declines dramatically across cohorts. Panels A, B, and C of Appendix Figure D.2b shows that the positive effect on y_ae_{it} for women is more similar across cohorts. As AGHV point out, some of the symmetry between the effects of marriage and divorce is an artifact of the model, which does not distinguish between divorced and never-married individuals in the wage, employment, and hours equations.

5.2.4 Accounting for Housework

Thus far we have shown that marriage and divorce have strong effects on $earn$, y, and y_ae, especially for women, and that gender differences in these effects have declined substantially across cohorts. AGHV attempt to account for the fact that the drop in work hours for women after marriage and children is a shift toward home production that husbands benefit from and, to a large extent, lose access to after a divorce. They assess the degree to which accounting for home production reduces gender differences in the estimated economic impact of marriage and divorce. To do so, they use PSID data on annual hours spent on housework by the sample member and the spouse if present. They value housework of both men and women at the 25th percentile of the female real wage distribution in their sample. They regress $\ln((Y_{it} + HW_{it} \cdot wage\_25)/AE_{it})$ and y_ae_{it} on MAR_{it} for a set of observations around a transition into marriage. They conclude that considering home production reduces the gap between men and women in the effect of marriage on economic resources per adult equivalent by about one quarter.

We employ this same strategy, except interacting MAR_{it} with birth cohort to examine the change across cohorts.[25] For brevity's sake, we do not report the complete regression results and instead focus on the main results. Our results indicate that, for the 35–44 cohort, considering home production reduces the gap in the effect of marriage on economic resources by about 0.15 log points. The corresponding values for the 45–62 and 67–80 cohorts are

[25] We take the 25th percentile of our entire PSID sample; we do not vary this value by cohort.

0.23 and 0.16, respectively. Considering housework, then, does most to close the gap in the economic impact of marriage for the middle cohort.

5.3 Unemployment Shocks

Figure 4 panels A, B, and C display the response of earnings and income for married women who worked positive hours at age 33 to an unemployment shock at age 34.[26] Keep in mind that an unemployment shock simply means that the person works positive hours but has some unemployment over the year. The solid dark blue line is the IRF for $earn_{it}$. For the 35–44 cohort (Panel A), $earn_{it}$ declines by -0.08, rebounds fairly quickly as hours recover, and returns to the baseline value in about 5 years.[27] The negative effects of the unemployment shock grow larger across cohorts. For the 67–80 cohort, $earn_{it}$ falls by -0.27. The growth in the earnings response is mirrored in an increase of the responses of $famearn_{it}$ and y_ae_{it}.

The corresponding IRFs for married men from the 35–44 cohort show a drop in $earn_{it}$ of -0.26 followed by a recovery to -0.06 at age 40 and -0.02 at age 45. The much larger earnings response for men than for women is mirrored in a much larger negative effect on y_ae_{it} and $famearn_{it}$. For married men in the 67–80 cohort the initial drop in $earn_{it}$ after an unemployment shock is even larger: -0.46. These results indicate that experiencing any unemployment during the year has a much stronger, negative impact on men's earnings in more recent cohorts. Interestingly, the magnitude of the effect on y_ae_{it} only increases from -0.18 for the 35–44 cohort to -0.26 for the 67–80 cohort even though the negative effect of unemployment on $earn_{it}$ increased by 0.2 log points across the same two cohorts. This reflects a key factor driving many of the cohort trends in this paper—the growing importance of wife's earnings.

Appendix Figure D.3 shows the effects of an unemployment shock for single women and single men. For the 1935–44 cohort, the effect on earnings is -0.15 for single women and -0.24 for single men. The effects on y_ae_{it} are -0.11 and -0.21. The effects are substantially more negative for both single women and single men in the 67–80 cohort. For example, for single men the effects are -0.39 for earnings and -0.34 for y_ae_{it}. Both single men and single women experience a larger percentage decline in y_ae in response to a shock than married individuals because they do not have the earnings of a spouse.

[26] Note that we only shock those who had positive hours but were experiencing no unemployment ($E_{it} = 1$) at age 34 in the baseline simulation.

[27] We have also produced IRFs for $hours_{it}$, $wage_{it}$, and E_{it} for the 12 gender, marital status and cohort combinations but do not report them. In all cases, the initial drop in earnings is entirely due to hours. The decline in $wage_{it}$ is smaller but more persistent. See AGHV.

5.4 Wage Shocks

Figure 5 reports the IRFs corresponding to a positive, one-standard-deviation innovation in the persistent wage component ω_{it} for married men and women. The shock is 0.186 at age 34 for both married and unmarried women and 0.183 for both married and unmarried men. The effect decays over time at a rate determined primarily by the gender-specific values of ρ^w_{it}. For married women, the effect on earnings is a mix of a labor supply effect and the direct wage effect. It is much larger than the y_ae_{it} response. The size of the earnings effect grows across cohorts, but the relative size of the effect on y_ae_{it} grows much more. Hence, although women's earnings in recent cohorts are only slightly more responsive to a shock to the persistent wage component, such a shock is more consequential for family income in the more recent cohorts as a result of women's increased prominence in the labor market.

For married men, the effect on earnings grows across cohorts from 0.18 to 0.2. The effect on y_ae_{it} is 0.13 for the 35–44 cohort. Notably, although the earnings effect grows slightly across cohorts, the effect of the wage shock for men on y_ae_{it} falls across cohorts, reaching 0.11 for the 67–80 cohort, once again reflecting the shifting contributions of male and female spouses in more recent cohorts. The estimates for unmarried women and men are more similar, and do not change much across cohorts. For women, the impact of the shocks on y_ae_{it} is closer to its impact on earnings (Appendix Figure D.4).

5.5 Effect of a Birth on Earnings and Family Income

We now turn to differences across cohorts in the dynamic effects of the birth of a child on earnings and income. Figure 6 panel D displays the IRF of $earn_{it}$ in response to a birth at age 34 for married women in the 35–44 cohort (solid blue line). Earnings fall by an average of -0.45 over the first five years and then recover slowly. Family earnings fall by only about -0.06 despite the large drop in $earn_{it}$. The disparity reflects the low family earnings share of young married women in the pre-baby boom cohort. Family earnings remain at about that level (relative to the baseline) for many years. Family income y_ae_{it} falls by about –0.22 reflecting the fact that the birth mechanically increases AE by 0.5, and stays there for many years.

The effect of a birth on the earnings path is less negative for the more recent cohorts. For the 67–80 cohort earnings fall by an average of -0.39 in the first five years after the birth. However, the negative effects on $famearn_{it}$ and y_ae_{it} are relatively stable across cohorts by comparison, as the rising female share of family earnings offsets the reduced magnitude of the earnings response.

Panels A, B, and C present corresponding IRFs for women who are single at age 33. For the 35-44 cohort, earnings fall by an average of -0.68 in the first five years and gradually recover, with the dynamics reflecting the coefficients on $CH05_{it}$, $CH612_{it}$, and $CH1318_{it}$. The IRFs for employment, the wage, and log hours (not shown) display large negative effects on hours and a substantial negative effect on the wage. Family earnings fall initially and then turn positive. The reason is that for the 35–44 cohort a birth increases the probability of being married by about 30 percentage points for both single women and single men, as shown in Appendix Figure D.5. For the same reason, y_ae_{it} falls by only -0.34 in the first five years after a birth, which is less than would be expected given the large earnings drop of -0.68. Panel C shows that for the 67-80 cohort the negative effect of the birth to a single woman on the path of earnings is much smaller: -0.33 on average in the 5 years after the birth. Furthermore, the drop in family earnings and y_ae_{it} is much closer to the drop in earnings, because for the post baby boom cohort the effect of the birth on MAR_{it} is only 0.05 after one year, peaking at 0.10 after 6 years. These patterns are, of course, directly related to the rise in the fraction of children raised by single mothers.

Turning to Appendix Figure D.6, for married men in the early cohort we find very small positive increases in $earn_{it}$ over the long run after a childbirth. Family earnings drop by a small amount while y_ae_{it} drops by about -0.25, primarily due to a mechanical effect on the adult equivalence scale. For unmarried men, the birth leads to an increase in earnings of about 0.04 over the first few years and a drop in y_ae_{it} of about -0.38. The latter drop is due to the effect of the child on entry into marriage as well as the mechanical effect on the adult equivalence scale.

For both married and single men in the 67–80 cohort, the birth leads to a gradual reduction in $earn$ by about -0.04 over the first ten years after the birth, followed by a recovery. Family earnings follow a similar path for single men, while for married men the fall in family earnings peaks in the first few years after childbirth and then gradually recovers. The fall in y_ae_{it} after childbirth is similar across cohorts. The big change across cohorts is that for the 67–80 group of single men, the marriage probability rises by a maximum of 10 percentage points in the years after the birth of the child.

What about the marriage and sorting channels? Appendix Figure D.7 panels A, B, and C show that for married women, the marriage channel increases the negative effect of birth on the path of y_ae_{it} by a modest amount in all three cohorts. With the marriage channel, the birth reduces divorce, which in turn reduces earnings from a spouse. The sorting channel makes little difference. The contribution of the two channels is qualitatively similar for married men, but smaller in magnitude (not shown).

Panel D of the same figure D.7 considers single women from the 35–44 cohort. Eliminating the marriage channel increases the negative effect of a birth on y_ae_{it} from -0.34 to -0.48 four years after the birth. The reason is that for this cohort a birth typically led to marriage. Eliminating the sorting channel reduces the negative effect by about 0.04. The marriage channel is much less important in the later cohorts (Appendix Figure D.7 panels E and F). We exclude the results for men to save space.

6 The Effects of Education and the Permanent Wage Component on Earnings and Family Income Over the Life Cycle

Next we examine generational change in the effects of education and of permanent wage heterogeneity on earnings and family income over the life cycle. To examine the effects of education, we use our model to first simulate a large number of individuals, setting years of education equal to 12 (equivalent to a high-school degree) for all individuals. We then simulate the model again, this time setting education to 16 (equivalent to a college degree) for everyone. We then compare, at each age, the difference in the mean of log earnings and in the mean of y_ae across the two simulations. In order to assess generational change, we do this separately for each gender-cohort group. To examine the effect of permanent unobserved heterogeneity in wages we follow a similar procedure, but where the first simulation sets the permanent wage component μ_i to its mean (zero) for all individuals, and the second simulation sets μ_i to its estimated (positive) standard deviation.

Figure 7 panels A, B, and C present the difference between the mean paths of earnings and y_ae_{it} for women with 16 years of education and women with only 12 years of education. The results in panel A are for the 35–44 cohort. The education gap in earnings rises from about 0.59 at age 30 to 0.91 at age 55 (blue solid line). Appendix Figure D.8 shows that education differentials in both hours and the wage contribute to the gap. The gap in hours is U-shaped reflecting the fact that more educated women have children later in life. The education differential in y_ae is also large throughout the lifecycle (Figure 7, dashed teal line). It rises from 0.43 at age 30 to 0.55 at age 55.

The middle cohort shows a similar pattern as women in the early cohort. Additionally, the data allow us to characterize the education earnings gap from ages 25 to 30. The picture that emerges is one in which at very young ages there was a large earnings gap as high-education women were less likely to be married and, therefore, more likely to participate in the labor market. The gap fell in the middle years as the more educated women married, had children, and reduced labor supply and earnings, before the gap begins to rise again. A similar though less dramatic pattern is evident in y_ae_{it}. The education gap fell in the late

30s and early 40s before rising back to (close to) its original level.

For the 67-80 cohort, the lifecycle patterns in the education gaps in earnings and y_ae_{it} were much more muted: women with 16 years of education consistently earned about 0.8 log points more than women with 12 years of education. The gap in y_ae_{it} started high—at about 0.64 at age 30—and rarely fell below 0.52 log points between ages 30-55. Compare this to the earlier cohorts, for which the gap in y_ae_{it} rarely *rose* above 0.54 log points.

Figure 7 panel D, E, and F report results for men. The earnings differential rises dramatically with age for all cohorts. For the 35-44 cohort the gap rises from 0.12 at age 25 to 0.82 at age 55. Later cohorts, however, see a higher earnings gap at every age. For the 67-80 cohort, the gap is 0.29 at age 25 and peaks at 0.95 at age 50. Almost all of the increase across cohorts is due to a substantial widening of the gap in hours prior to age 50. (Appendix Figure D.8). For men the education gap in y_ae at age 25 increases from 0.18 for the early cohort to about 0.4 for the later cohorts. The values at age 50 are 0.50, 0.50, and 0.60 for the 35-44, 45-62, and 67-80 cohorts respectively.

Figure 8 panel A shows that, for the 35-44 cohort, eliminating the marriage channel has little effect on the female college-to-high school differential in the path of (y_ae). Eliminating both the sorting and the marriage channels reduces the education differential by an amount that increases from about 0.16 at age 30 to about 0.20 in the early 50s (the difference between the solid black line and the dot-dash green line). Almost all of the effect is from sorting. The 0.20 reduction is very large relative to the base of about 0.6. Turning to the 67–80 cohort in panel C, one can see that the contribution of sorting varies greatly over the lifecycle. It contributes about 0.12 of the education differential at age 30, 0.18 at age 40, and an average of about 0.14 after age 50. Thus positive assortative mating plays a critical role in the economic return to education for women, although it is less important for more recent cohorts of women, who marry less and work more. The contribution of the marriage channel grows across cohorts but remains modest relative to the sorting channel.

For men in the 35-44 cohort, (panels D), eliminating sorting channel reduces the college-to-high school differential in y_ae by an amount that rises from 0.04 at age 30 to and rises to about 0.09 at age 55. Thus assortative mating by education matters considerably more for women, largely because married women contribute a smaller share of family income. However, the gender gap in the importance of assortative mating is much smaller in the 67-80 cohort.

Figure 9 reports the effect of a one-standard-deviation increase in the permanent wage component μ from its mean of 0 on the average paths of *earn* and y_ae. The standard deviations of μ are 0.33 for women and 0.35 for men. Panel A is for women from the pre-baby boom cohort. The solid blue line shows that the mean of *earn* for high-μ women gradually grows from 0.18 above the value for average-μ women at age 30 to 0.28 at age 50. Hours differences account for about 1/4 of the earnings gap (not shown). The education gap in earnings averages about 0.29 for the 45-62 cohort and 0.33 for the 67-80 cohort, likely reflecting an interaction between higher wage potential and higher labor force participation in the more recent cohorts. The dashed teal lines show the effect of a one-standard-deviation increase in μ on the path of y_ae_{it}. The effect increases across cohorts from a lifetime average of about 0.18 for women in the 35-44 cohort to 0.25 for women in the 67-80 cohort.

The patterns for men in Figure 9 panel D show that high-μ men earn about 0.34 more than average-μ men over the life cycle in the early cohort, which is well above the corresponding value for women. The size of the effect increases across cohorts, as was the case for women, but the increase is smaller. The effect of μ on the path of y_ae_{it} increases only slightly averaging across ages, but the decline in the effect with age becomes smaller. Note that the change in slope reflects many factors, including marriage profiles, labor supply behavior of married women, and male labor supply.

For women in the 35–44 cohort, eliminating both the sorting and marriage channels lowers the gain in y_ae_{it} from a one-standard-deviation increase in μ from about 0.18 to about 0.12 (Appendix Figure D.9, Panel A). The lion's share of the reduction is due to eliminating sorting. The contribution of the sorting channel declines by a small amount across cohorts. For men, eliminating the two channels reduces the effect of μ by about 0.01 early in life and about 0.03 at age 45 (Appendix Figure D.9, Panel D). Most of the reduction is from eliminating sorting, as was the case for women, but the reduction is considerably smaller, especially as a percentage of the overall effect of μ. The contribution of sorting increases slightly across cohorts, while the marriage channel contributes about 0.01 after age 45 for the most recent cohort.

7 Variance Decompositions of Labor Market Outcomes and Income over a Lifetime

In this section we use our model to decompose, separately for each gender-cohort group, the variance (across individuals in that group) of y_ae into the contributions of several sources of variation. We use the same sources of variation as in AGHV (save for the addition of i.i.d. wage shocks to the model). These sources of variation are: (1) education; (2) the permanent wage component μ_i; (3) the permanent employment component ν_i and hours component η_i; (4) the i.i.d. shocks to employment status plus variation in initial employment conditional on education, marital status, and number of children; (5) 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}; (6) 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}; (7) the initial draw and shocks to the autoregressive component of unearned income; (8) the random component $\varepsilon^{ED_s}_{it}$ of the spouse's education; (9) the random component $\tilde{\mu}^s_i$ of μ_{si}; (10) η_{si} and ν_{si}; (11) 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}; and (12) 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]

7.1 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 55. We use the simulated data to compute each individual's annual average, from age 25 to 55, of y_ae, and then compute the variance (across individuals in that group) of those lifetime averages.[30] Next we simulate the model again, but this time shutting down the variance of a particular random component in the model (e.g. setting the permanent wage component μ_i to 0), and we use the difference in the variance of the lifetime averages, relative to the base case simulation, as the contribution of that particular source of variation. We do this for each source of variation, one at a time.[31]

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. Note first that an individual's marital history between ages 25 and 55 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 55. For each simulated life, we construct the categorical variable $MHIST_i$ that contains this information.

If all of the effects were additive and linear, we could first regress lifetime income on the simulated values of all variables except marriage history and then measure the marginal contribution to the explained variance (corrected for degrees of freedom) by adding fixed

[28]Of course, the importance of the spouse's components will depend on the amount of time an individual spends married.

[29]Our methodology is the same as in AGHV and the discussion of the methods here borrows from that paper, sometimes verbatim.

[30]Here we focus on the lifetime average of y_ae (as well as other outcome variables). We have also experimented with decompositions of the variances of the log of the lifetime sums of the levels of the outcome variables (not reported), obtaining broadly similar results. (See also the discussion in Section 6.1 of AGHV.)

[31]For education, we shut down its variance by setting $EDUC_i$ to its mean by gender and birth cohort, and condition only on gender and cohort when drawing the initial values of employment, marriage, and number of children at age 25. For labor force status, we shut down employment status shocks by setting E_{it}, U_{it}, and N_{it} to their predicted probabilities conditional on the variables in the employment status model, including ν_i, but with the shocks set to 0.

effects for each unique value of $MHIST_i$. 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 and AGHV found that wage and employment shocks have only a moderate influence on marriage transitions.

7.2 Lifetime Variance Decompositions of Family Income Per Adult Equivalent

The variance decompositions of lifetime y_ae by gender and cohort group are presented in Figures 10 and 11. Figure 10 displays the contributions of the sample members' own characteristics and shocks (e.g. EDUC$_i$ and μ_i,), while Figure 11 shows the contributions of random variation in marital histories and random variation in spouse characteristics. In both figures, the red bars correspond to women and the blue bars to men, with darker shading corresponding to older cohort groups. The height of the colored bars denotes the percent of the variance in lifetime y_ae that is explained by a particular source of variation. (The corresponding numerical value is displayed above the bars.) The error bars denote 90 percent confidence bands. Appendix Tables E.1-E.3 show similar variance decompositions for a few additional lifetime outcome variables, including the lifetime average of the logs of earnings, hourly wages, work hours, family earnings, unearned income, and family income.[32]

Starting with Figure 10, the first set of bars shows the contribution of variation in education to the variance of lifetime y_ae. Consistent with AGHV, education plays a very important role for both men and women and for all cohort groups, contributing between 25.8 and 38.1 percent of the variance of lifetime y_ae. The figure also shows that the difference between men and women in the role of own education has narrowed over time. For the 35-44 cohorts, the variance contribution was notably larger for men than for women (38.1 versus 33.3 percent), whereas for the 67-80 cohorts, the contribution of education is similar (31.1 percent for men and 30.1 percent for women). Note that the contributions shown here capture all of the channels by which education affects lifetime family income in the model, including not just through own earnings, but also through marriage and spousal earnings (via marital sorting).

The second set of bars in Figure 10 displays the variance contribution of the permanent

[32] Note that the variance of lifetime y_ae differs across gender and cohort groups. For example, as Appendix tables E.1-E.3 show (column 15, bottom row), the standard deviation of lifetime y_ae increased from 0.54 for women in the 35-44 cohorts to 0.59 for women in the 67-80 cohorts, and from 0.53 for men in the 35-44 cohorts to 0.61 for men in the 67-80 cohorts. In the case of lifetime earnings (first row of the tables), the standard deviation is much higher for women than for men for all cohort groups.

wage component μ_i. Variable μ_i is also very important, contributing between 14.5 and 26.8 percent of the variance of lifetime y_ae. Consistent with AGHV, we find that μ_i plays a larger role for men than for women. However, as in the case of education, the difference between men and women has narrowed over time. As the figure shows, the importance of μ_i for women has increased steadily, rising from 14.5 percent for women in the 35–44 cohorts to 20.6 percent for those in the 67–80 cohorts. The increase in the contribution of μ_i reflects at least in part the increased participation of women in the labor force and the corresponding larger contribution of women's earnings to overall family income in more recent cohorts. By contrast, the importance of μ_i for men has declined slightly over time, likely due to the small increase in nonparticipation for men in more recent cohorts. All told, the gap in the variance contribution of μ_i between men and women has shrunk from 12.1 percentage points for the 35-44 cohorts to just 2.6 percentage points for the 67-80 cohorts.

The next set of bars show a large increase across cohorts in the combined contribution of the permanent employment component ν_i and hours component η_i. Their variance contribution has risen from 6.6 in the early cohort to 17.9 in the later cohort for women; for men, the contribution of η_i and v_i has risen from 8.9 to 27.2. The increase for women likely results from their increased participation in the labor force and the larger share of family income that women's earnings comprise for more recent generations. For men, the increase likely stems from a completely different force: the drop in male labor force participation.[33] As men as a group became less permanently attached to the labor force, variation in η_i and v_i began to play a much larger role in determining nonparticipation.[34]

The last three sets of bars in Figure 10 show the contributions of the transitory shocks to each of: wages, hours, and employment. Compared to the permanent components previously discussed, the variance contributions of these sources of variation to the variance in y_ae are relatively smaller, in large part because these components are transitory in nature, and their effect consequently fades over the course of a lifetime.[35] That said, the importance of shocks to the wage component ω_{it} has increased somewhat for women in more recent birth cohorts,

[33]See, for example, Appendix Figure C.2, showing that nonparticipation (zero work hours during the year) was nearly nonexistent for young men in early life in the 1935–1944 cohort while in the 1967–1980 cohort at least 4% of men at every age report nonparticipation.

[34]Recall from 3.2.2 that in order to better fit persistence in employment, we restricted the variance of v_i to be twice the unrestricted MLE estimate. We re-estimated the employment model without the constraint on v_i, and used this new employment model (keeping all other models the same) to perform the variance decomposition. We find that while our constraint on v_i raises the estimated *level* of the variance contribution of v_i and η_i, it does not do much to explain the *trend*. In our re-estimated decomposition, women saw the contribution of these factors increase from 4.0 to 13.0 across cohorts. The corresponding figures for men were 5.0 and 20.9.

[35]Note that, even in the case of the wage, the autoregressive coefficient of ω_{it} is only between 0.77 and 0.81; see Appendix Table B.1b.

with the variance contribution rising from about 1 percent for the earlier cohorts to about 3 percent for the more recent cohorts. This increase is also consistent with women's increased participation in the labor market and the larger share of women's earnings in overall family income.

Turning to Figure 11, the first set of bars shows the variance contribution of random variation in marital histories. Note that these contributions are net of the variation in marriage patterns that is explained by permanent characteristics. For women, the marital history contribution is 4.1, 5,8, and 4.7 for the early, baby boom, and later cohort. For men, the contribution has fallen somewhat, from 5.2 percent for the 35-44 cohorts to 2.5 percent for the 67–80 cohorts. Overall, variation in marital histories matters a little more for women than for men.

The remaining sets of bars in Figure 11 show the variance contributions of the spouse's education, the spouse's permanent wage component, the spouse's autoregressive wage component, and the spouse's permanent employment and hours components. Overall, the contributions of spouse characteristics have declined over time for women and increased for men. In particular, the variance contributions of spouses' education, μ_{si}, and ω_{sit} components are all smaller for women in the 67–80 cohorts than for women in the 35–44 cohorts. For men, by contrast, the contributions of spouses' education, permanent wage component, and permanent employment and hours components are all a bit larger for men in the 67–80 cohorts than for men in the 35–44 cohorts. The main exception to this pattern is the contribution of spouses' permanent employment and hours components for women, which has increased over time, likely as a result of the overall increase in the importance of these components for men.

Overall, the results in this section suggest that as gender roles have changed, with women's labor force participation increasing (along with marriage rates falling), own characteristics have become increasingly important in the determination of lifetime family income for women in more recent cohorts, while variation in spouse characteristics has become less important—all of this contributing to some narrowing of the gender gap.

7.3 The Role of Marital Sorting in Lifetime Inequality

How much higher/lower would lifetime inequality be if marriage partners were matched purely randomly? In this section we use counterfactual simulations of our model to assess the overall contribution of marital sorting to inequality in lifetime family income and to explore how this contribution has changed over time. Specifically, for each of our gender-cohort groups we run a counterfactual simulation in which $EDUC_{si}$, μ_{si}, and ω_{si} are drawn at random from their corresponding marginal distributions. We then compute the contribution of sorting (for each gender-cohort group) as the difference between the variance of lifetime y_ae with sorting (our base case simulation) and the variance under random matching, divided by the variance under random matching.

The results are shown in columns (1)-(4) of Appendix Table E.4. For women (lower panel), marital sorting increases the variance of lifetime income (per adult equivalent) by about 15 percent on average (column 4). Most of this is due to sorting on education (column 1), though sorting on μ_i (column 2) also plays a role. Comparing across cohorts, we see that the contribution of sorting on education has fallen some (from 12.6 percent for the 35–44 cohorts to 9.4 percent for the 67–80 cohorts), while the contribution of sorting on μ_i has increased some (from 2.9 percent for the 35–44 cohorts to 4.7 percent for the 67–80 cohorts). On net, the overall contribution of sorting (column 4) has fallen somewhat (from 17.8 percent to 12.9 percent).[36]

8 Concluding Remarks

The family income stream that an adult receives depends on own earnings and on the earnings of other household members. The weight on the two is affected by gender roles and marriage patterns. Consequently, the well-documented partial convergence between men and women in labor market behavior and decline in marriage rates and fertility has implications not only for gender differences in the average lifetime profiles of earnings and family income. It also has implications for gender differences in the dynamics and distribution of family income.

This paper extends the model and data in Altonji, Giraldo, Hynsjö, and Vidangos (2022) to permit investigation of generational change in adult family income processes. Rather than repeat the summary of results in the introduction, we emphasize three main themes. The first concerns shocks. Our overall finding is that the large asymmetries between men and women in the effects of divorce, marriage, own unemployment, wage shocks, and shocks to spouse's earnings on the path of family income declined substantially between the 1935–1944, 1945–1962, and 1967–1980 cohorts. The effects of divorce on family earnings and family income per adult equivalent become less negative for women and more negative for men. The same is true of gender differences in the effects of own unemployment and wage shocks to married individuals.

The second theme is that the large gender gap in the role played by marital sorting in the

[36]Recall however that the contribution of education, μ_i, and ω_i to the variance of lifetime income (per adult equivalent) is not the same across cohorts. For ease of reference, columns (5)-(7) in Table E.4 reproduces the contribution of these components to the variance of lifetime income (per adult equivalent) from tables E.1-E.3.

effects of education and the permanent component of wages on family income has declined substantially across cohorts. As married women work more, they account for a larger share of family earnings. This reduces the importance of sorting for women by a small amount and increases it substantially for men.

Finally, we find substantial changes in the variance decompositions of average annual family income per capita between the ages of 25 and 55. First, the gender difference in the importance of one's own education and the permanent wage component narrowed substantially. For the 1935–44 cohort, the variance contribution was 38.1% for men versus 33.3% for women, whereas for the 1967–80 cohort, the contribution of education is very similar (31.1% for men and 30.1% for women). The gender gap in the variance contribution of the permanent wage component declined from 12.1% for the 1935–44 cohort to just 3.4% for the 1967–80 cohort. The relative increase in the contributions of education and the permanent wage for women reflects at least in part the increased participation of women in the labor force and the corresponding larger share for more recent cohorts in women's earnings in family income. The flip side is that we find substantial gender convergence in the importance of random variation in whom one marries. For women, the combined variance contributions of random variation in spouse's education, the spouse's permanent wage component, the spouse's autoregressive wage component, and the permanent employment and hours components declined from 25.8% for the 1935–44 cohort to 20.2% for the 1967–80 cohort. For men, the corresponding values are 9.2% and 13.1%.

Much work remains to be done, beyond improving on the model, data, and estimation strategies. First, while we use the word "shocks", we provide no information about how much of the variability that we document is unanticipated and how much is uninsured. Doing so would require consumption data and/or expectations data.[37] Second, we have distinguished single adults and couples, but households have other adult family members. How have the transitions of adults into household with parents, adult children, and other nonspousal members changed? How has that affected the dynamics and distribution of the resources an individual has access to during adulthood? We leave these questions to future research.

[37]See Blundell, Pistaferri, and Preston (2008), Blundell, Graber, and Mogstad (2015), and Blundell, Pistaferri, and Saporta-Eksten (2016). It could differ across cohorts for a number reasons, including changes in social insurance and changes in credit markets.

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Figure 1: Response of Hours, Wage, and Earnings to a Divorce Shock

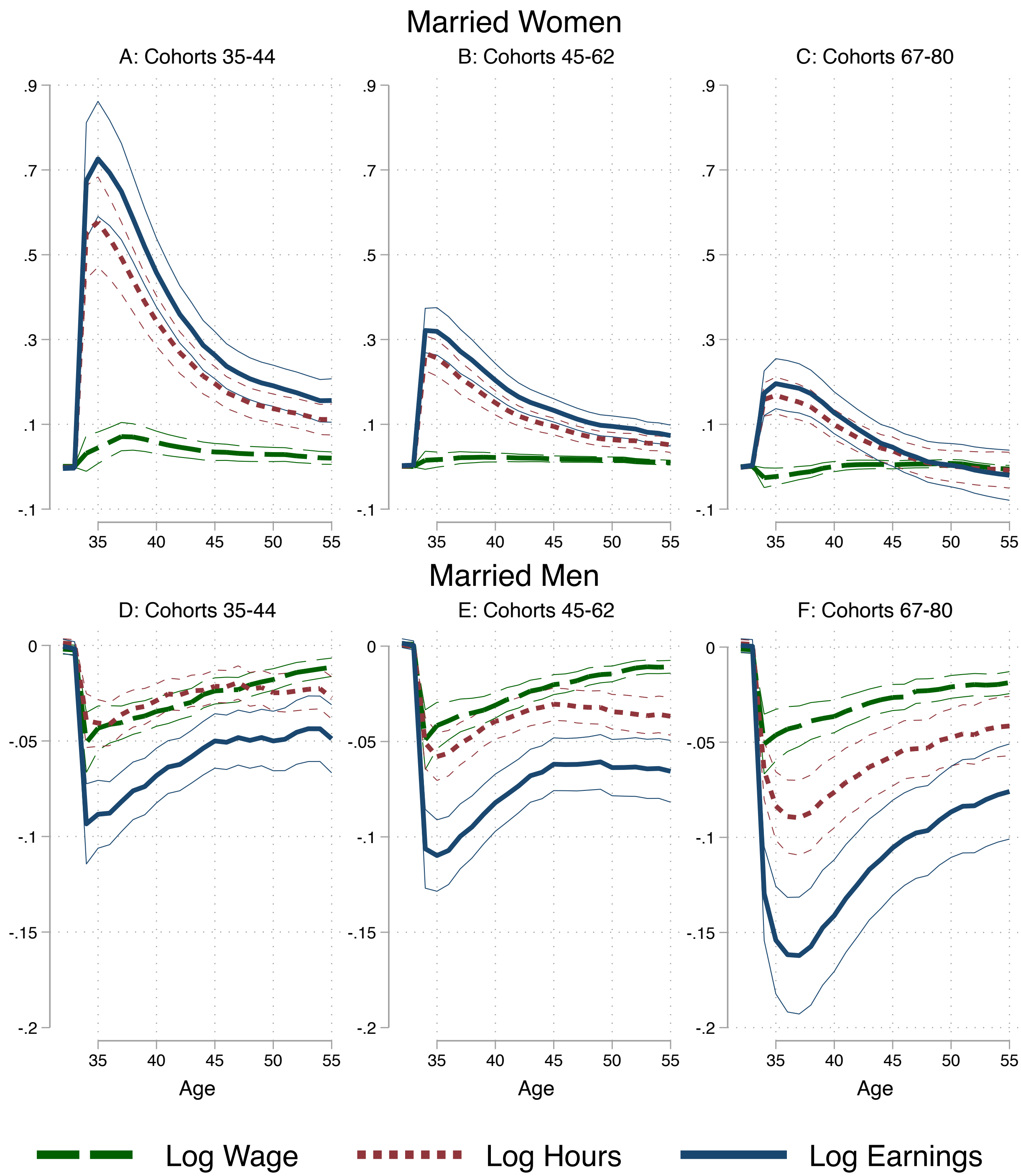


Figure 1 displays the effect of exogenously imposing a divorce shock on labor market variables. Panels A, B, and C focus on married women; D, E, and F show the results for men. The analysis is performed separately by cohort. Panel pair A and D show the results for those born from 1935 to 1944. B and E display the results for those born from 1945 to 1962, and C and F the results for those born from 1967 to 1980. The solid line shows the effect on earnings, the short dashes refer to hours, and the long dashes to wages. The thick lines trace out the point estimates, and the thinner lines, with corresponding patterns, trace 90% confidence bands. To obtain the results, we first simulate the lives of 500 copies per PSID sample member according to the model estimates. For this baseline simulation, and separately by cohort and gender, we compute the average values of each outcome variable for each displayed age for individuals who are married at age 34. We then perform the same simulation and calculation, but this time imposing that each married individual at age 34 is divorced. The presented estimates trace out the per-age difference in the average value of each variable between this second simulation and the baseline simulation. Note that the scales of the top row of panels are not the same as those of the bottom row. Confidence bands are obtained by performing 500 bootstrap simulations.

Figure 2: Response of Family Earnings and Family Income Per Adult Equivalent to a Divorce Shock

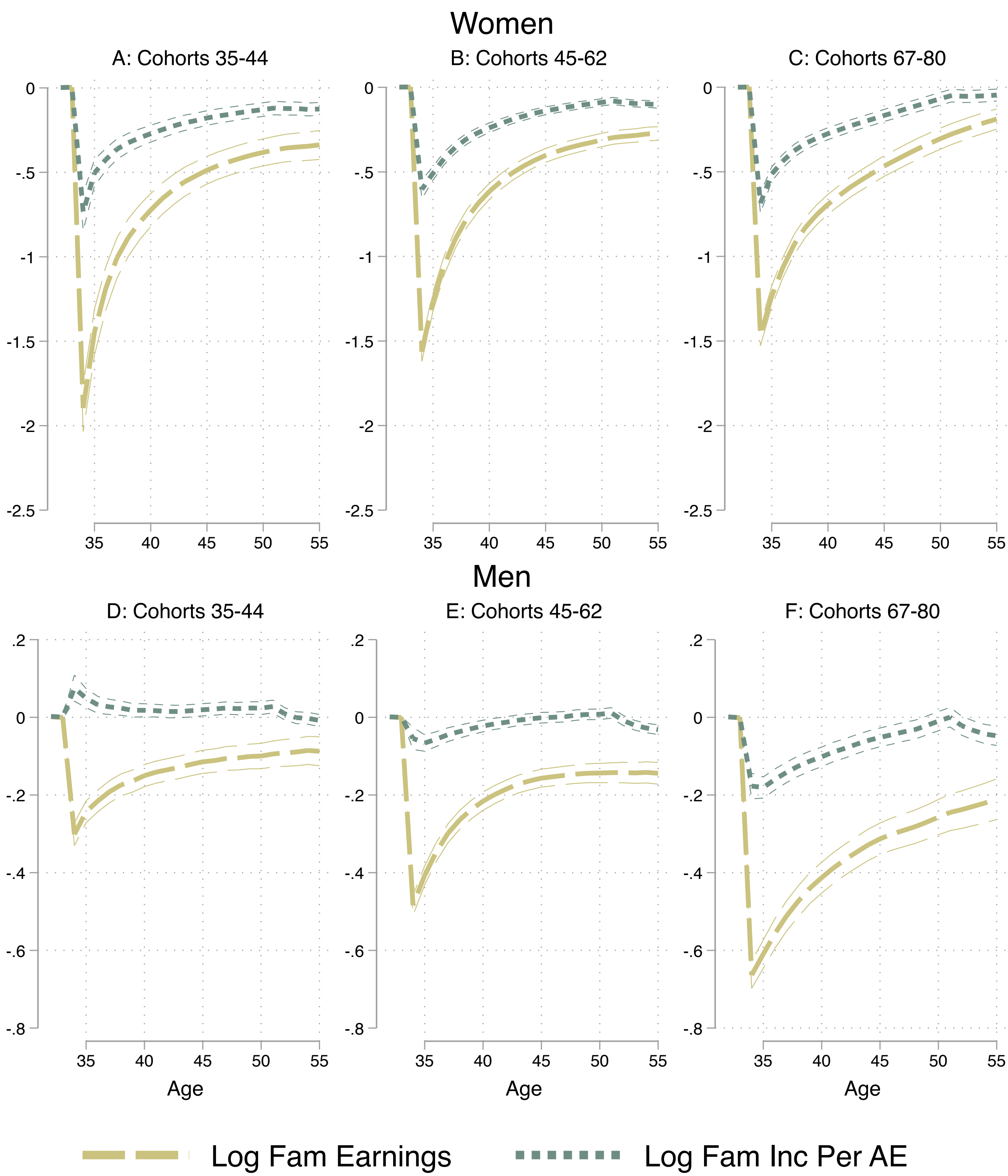


Figure 2 displays the effect of exogenously imposing a divorce shock on household income and earnings variables. Panels A, B, and C focus on married women; D, E, and F show the results for men. The analysis is peformed separately by cohort. Panel pair A and D show the results for those born from 1935 to 1944. B and E display the results for those born from 1945 to 1962, and C and F the results for those born from 1967 to 1980. The long dashes show the effect on family earnings, and the short dashes refer to family income per adult equivalent. The thick lines trace out the point estimates, and the thinner lines, with corresponding patterns, trace 90% confidence bands. To obtain the results, we use the same method as explained in the note to figure 1.

Figure 3: The Role of Marriage and Sorting in the Response of Family Income Per Adult Equivalent to Divorce

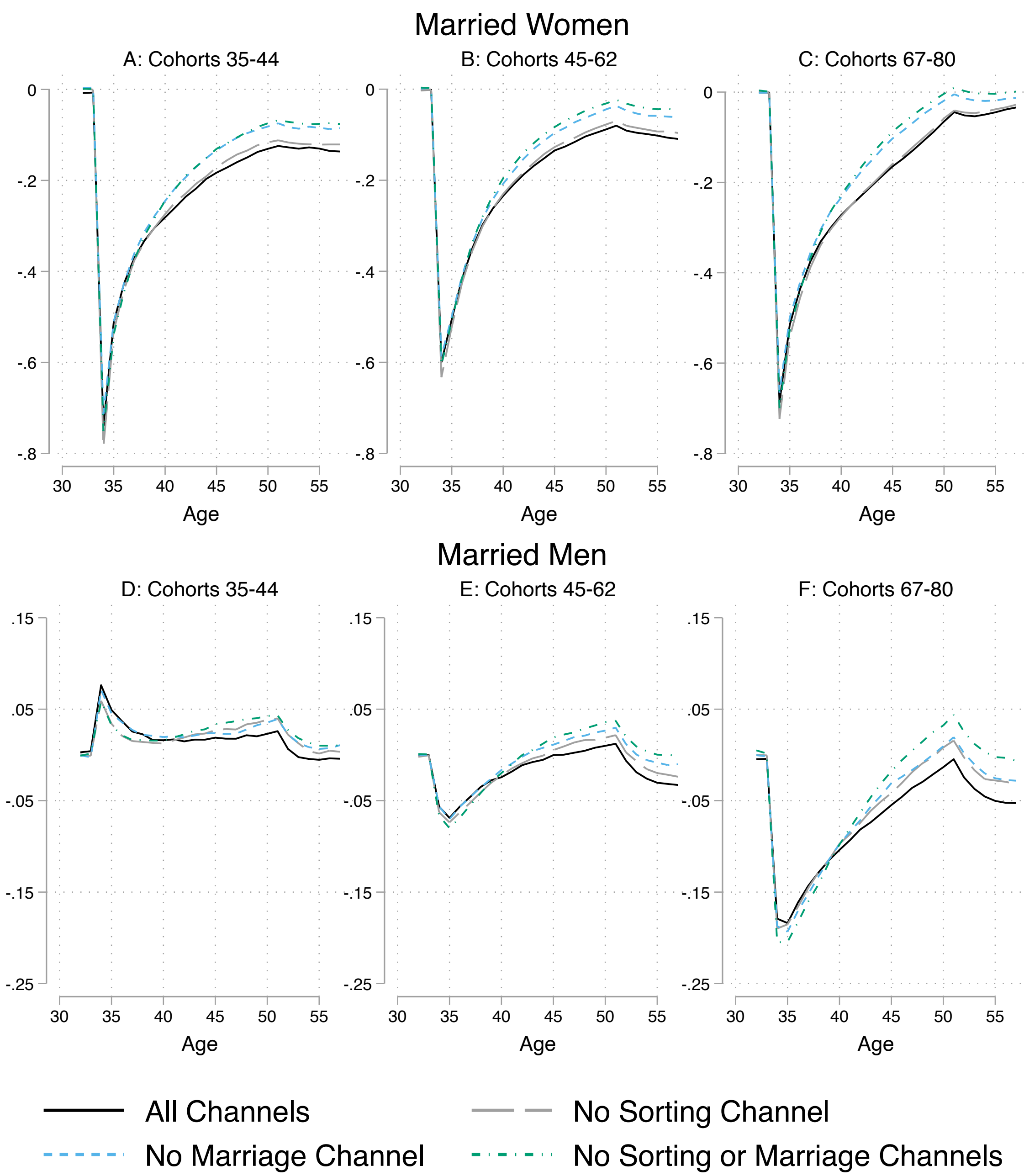


Figure 3 displays the contribution of marriage and sorting in explaining the effect of a divorce shock on family income per adult equivalent. Panels A, B, and C focus on married women; D, E, and F show the results for men. The solid lines black lines are identical to the dashed teal lines in Figure 2. That is, the solid lines trace out the effect of exogenously imposing a divorce shock on all married women and men by comparing average family income per adult equivalent in a baseline simulation and a simulation in which divorce is imposed on all married individuals at age 34 (see notes to figure 1). In figure 3, the difference between the solid black line and the the long-dashed gray line should be interpreted as the role of marital sorting in explaining the effect of divorce on family income. To obtain the "No Sorting" estimates, we use the same method as when obtaining the"All Channels" line, except we use a version of the marital sorting model which is meant to capture "no sorting" in the marriage market. In specifying this model, we allow partner characteristics to be only functions of polynomials in age, year, and cohorts, as opposed to other demographics and labor market variables. We estimate the parameters of the "no sorting" model by using simulated data from the original model. The lines with long dashes thus trace out the difference between average family income values per age when divorce is and is not imposed, in an environment where there is no sorting in the marriage market. Equivalently, we obtain the "No Marriage" line (short-dashed, light blue) by replacing the entry into marriage and marriage continuation models with models that allow the probability of these events to depend only on age, year, and cohort polynomials. The parameters for these models were also estimated using data simulated from the original model. The lines that combine dots and long dashes trace out the effect of a divorce shock when replacing both the sorting and marriage models with these alternative models. Note that the scales in the top row panels are not the same as those for the bottom panels.

Figure 4: Response of Earnings, Family Earnings, and Family Income Per Adult Equivalent to an Unemployment Shock

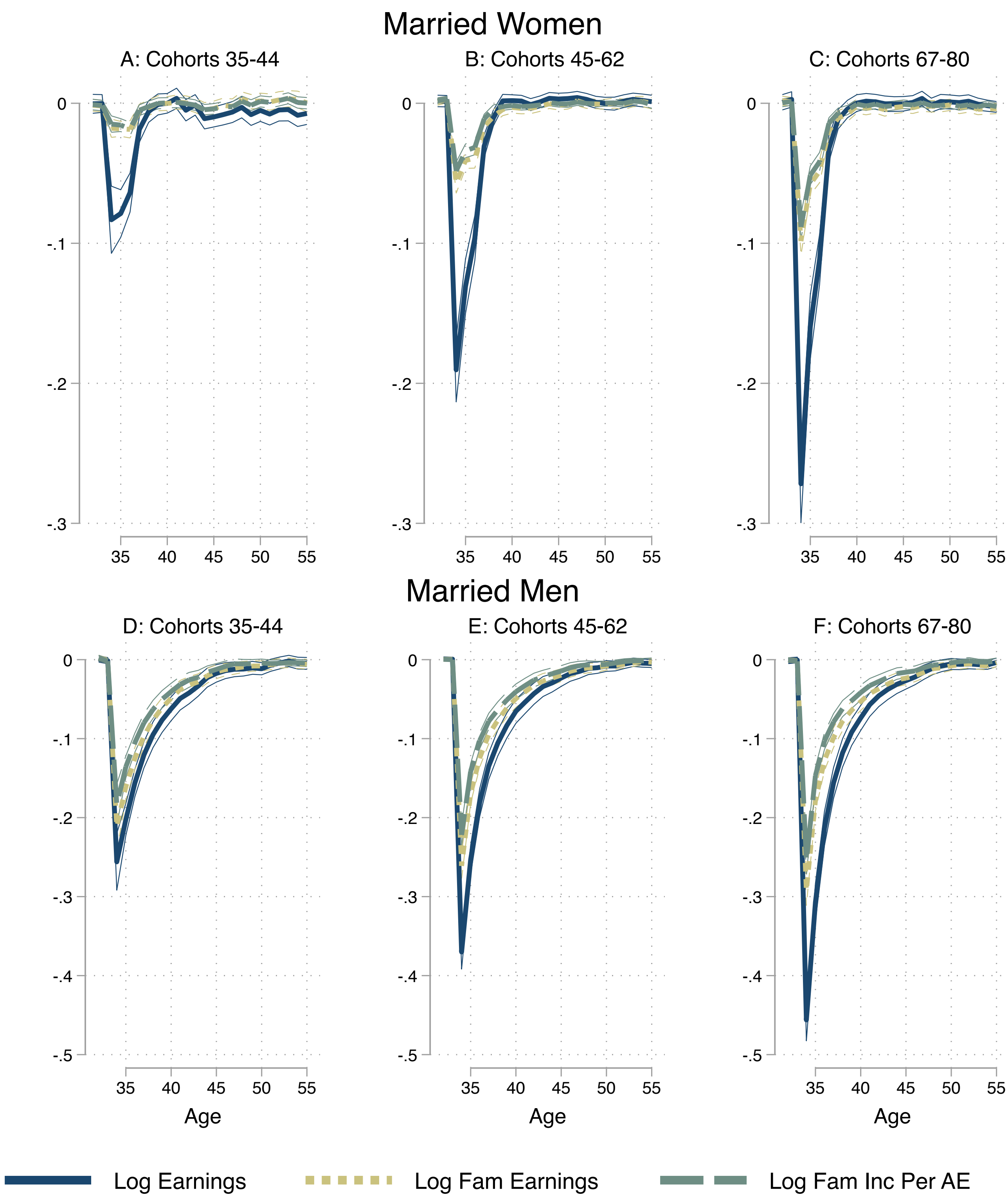


Figure 4 displays the effect of an exogenously imposed unemployment shock on married women and men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead that all individuals in the labor force become unemployed at age 34.

Figure 5 : Response of Earnings, Family Earnings and Family Income Per Adult Equivalent to a Wage Shock

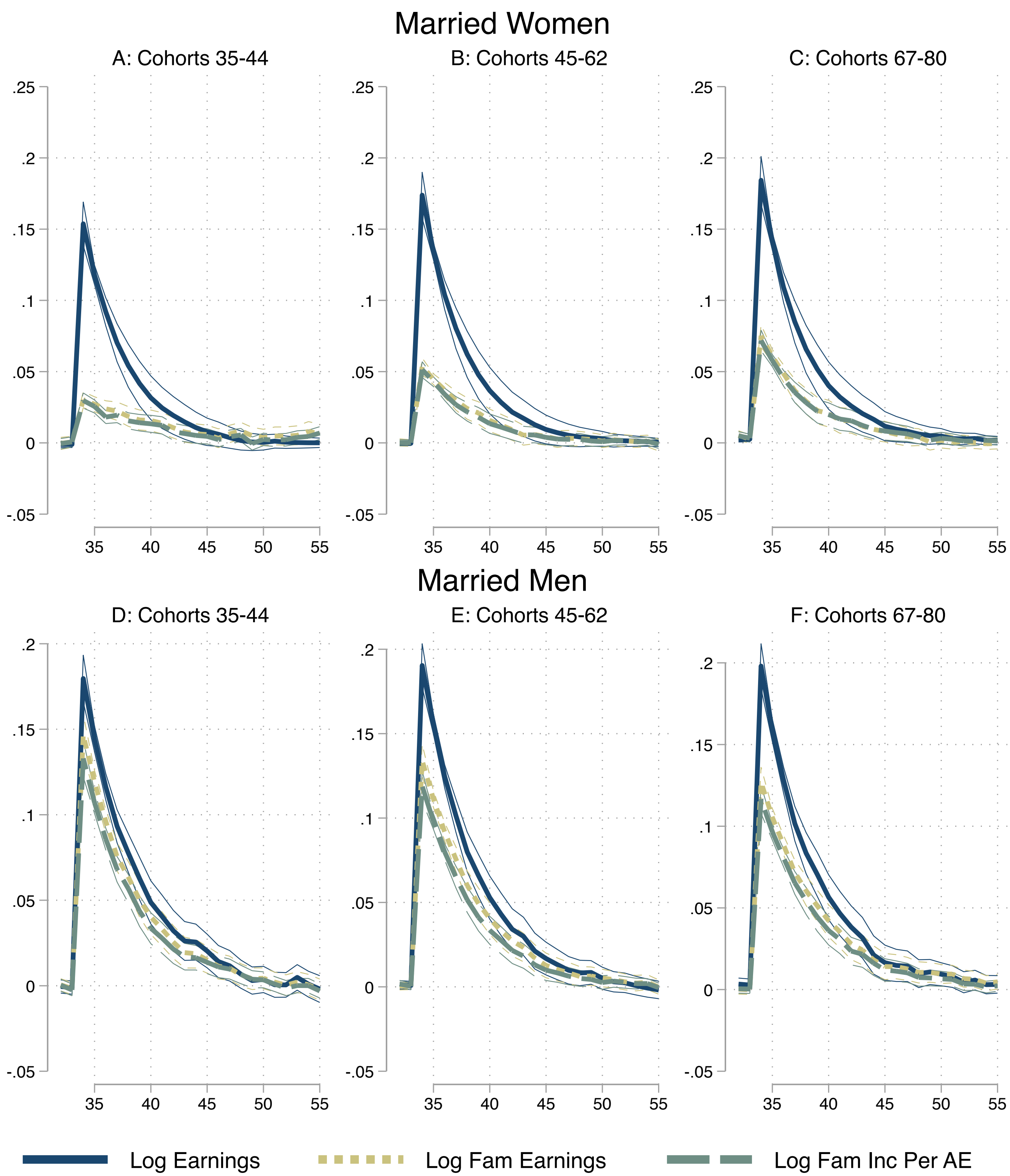


Figure 5 displays the effect of an exogenously imposed wage shock on married women and men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead a 1 SD increase in the autoregressive component of wages on all individuals at age 34.

Figure 6: Response of Earnings, Family Earnings, and Family Income Per Adult Equivalent to a Childbirth Shock

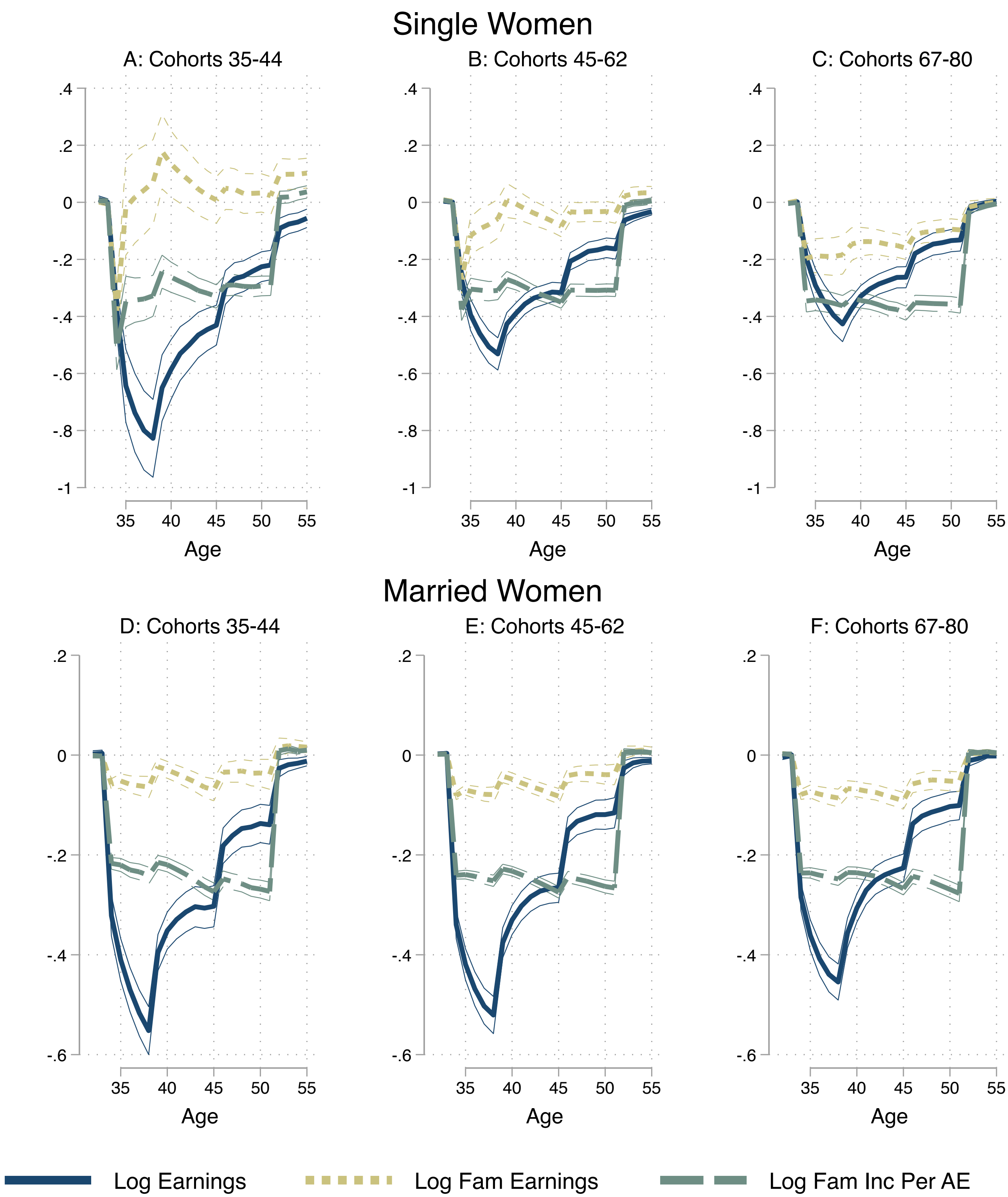


Figure 6 displays the effect of an exogenously imposed childbirth shock on single and married women. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead that all individuals have a child at age 34.

Figure 7: College - High School Gap in Earnings and Family Income Per Adult Equivalent

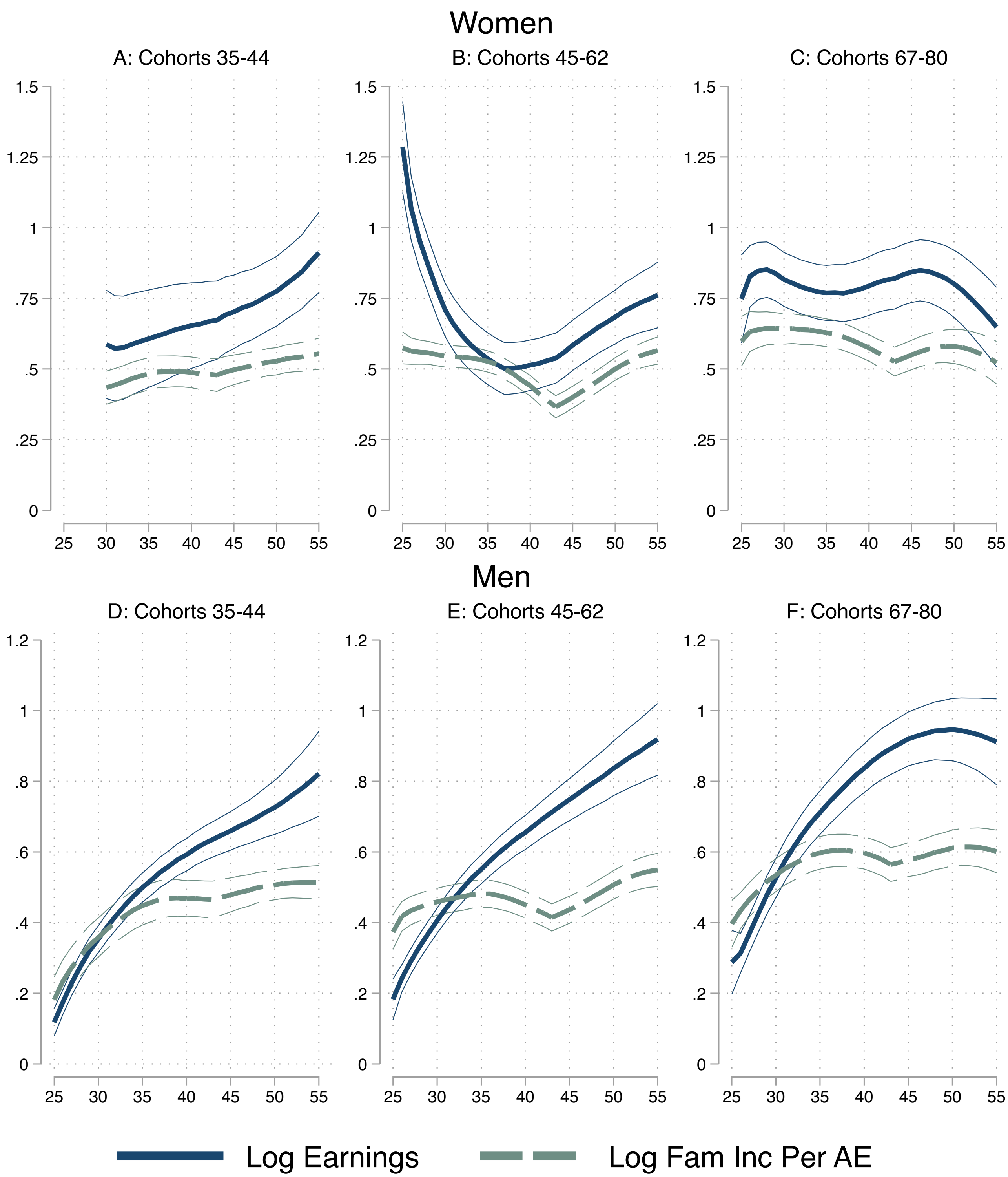


Figure 7 displays the difference in average earnings and log family income per adult equivalent experienced by women and men, at each age, imposing that all individuals have a college degree versus a high school education. To obtain the estimates, we first simulate the lives of 500 copies per PSID sample member according to the model estimates, with the exception that all simulated individuals are restricted to have a high school education. Then, we repeat the procedure, except imposing that all simulated individuals have a college education. We display the per-age difference between these two simulations in the average value of each variable. 90% confidence bands are obtained by performing 500 bootstrap simulations.

Figure 8: The Role of Marriage and Sorting in the College - High School Gap in Family Income Per Adult Equivalent

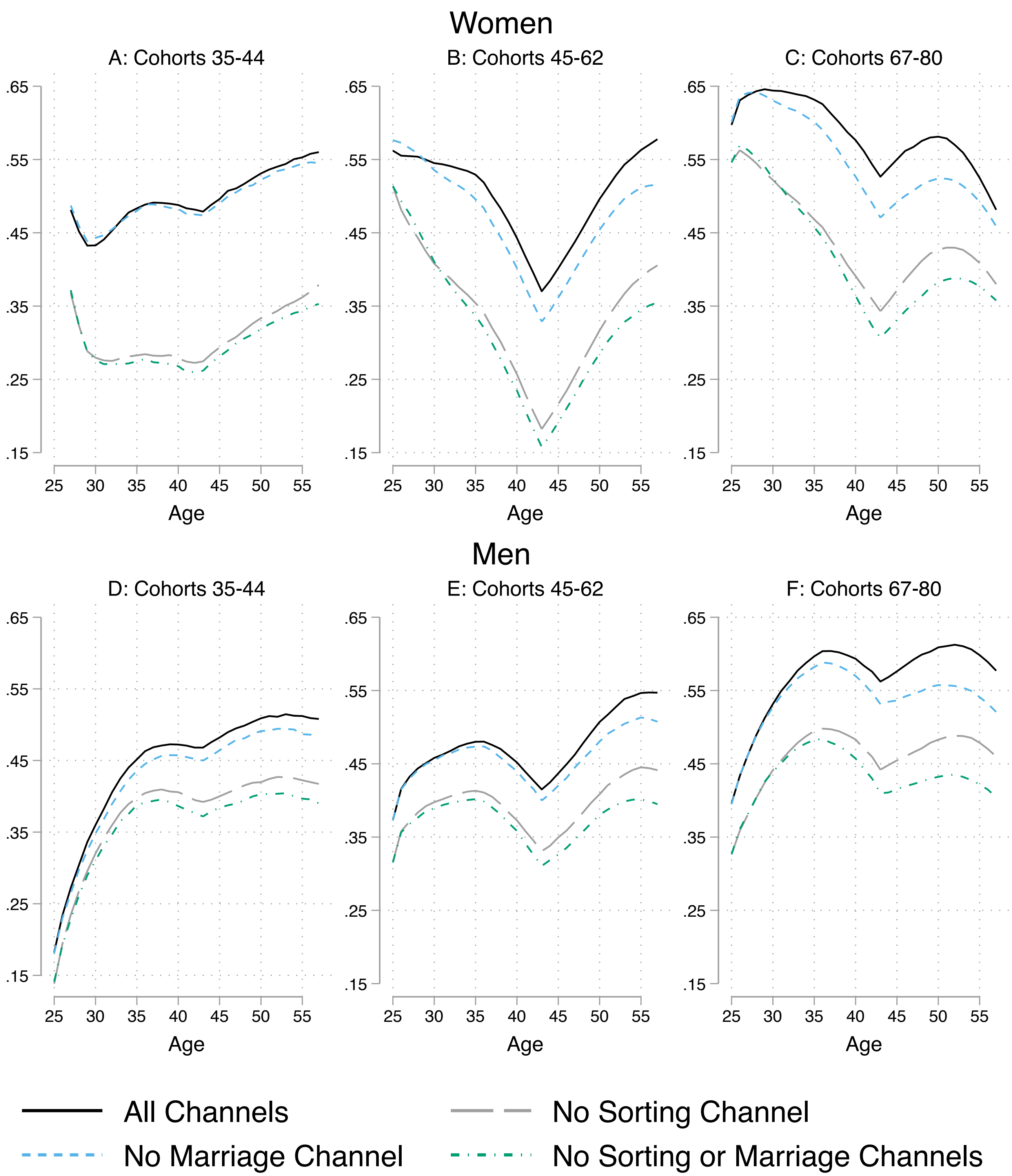


Figure 8 displays the role of marriage and sorting in explaining the effect of the college-high school in family income per adult equivalent. To obtain these estimates, we use the method as explained in the note to figure 3, but instead considering the role of turning off each channel in the difference in log family income per adult equivalent experienced by college and high school graduates over the lifecycle.

Figure 9: Permanent Wage Gap Effect on Earnings and Family Income Per Adult Equivalent

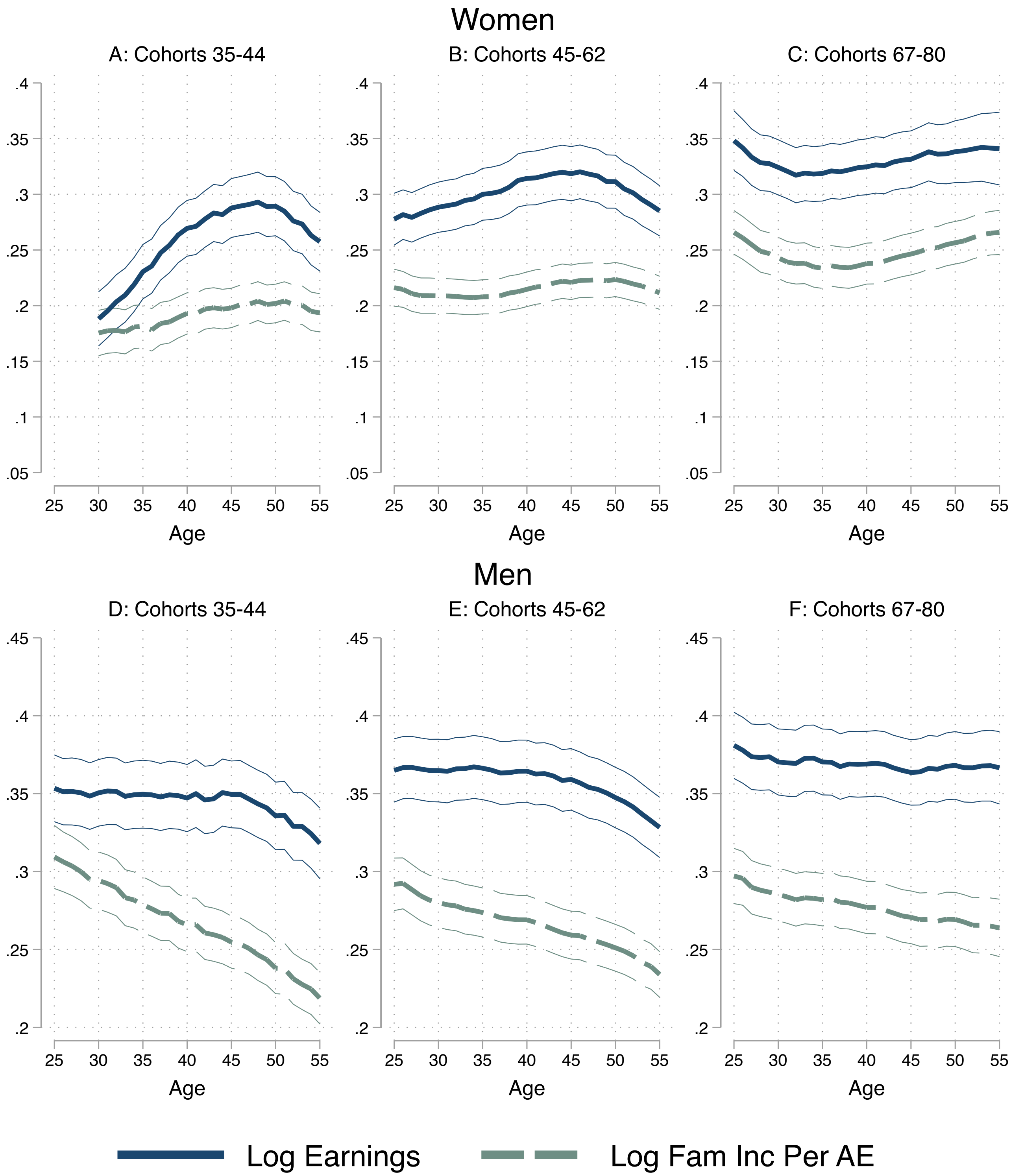
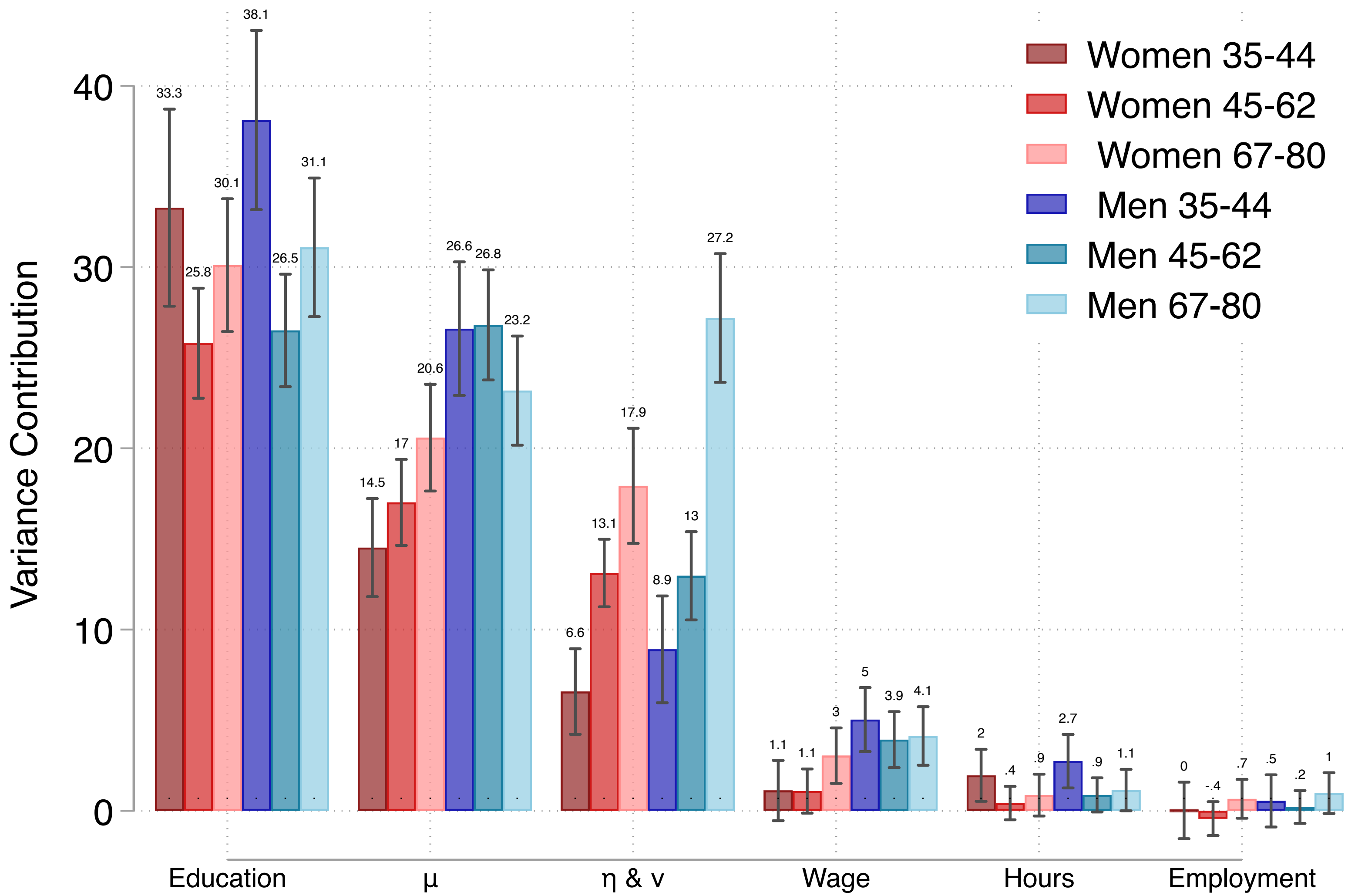


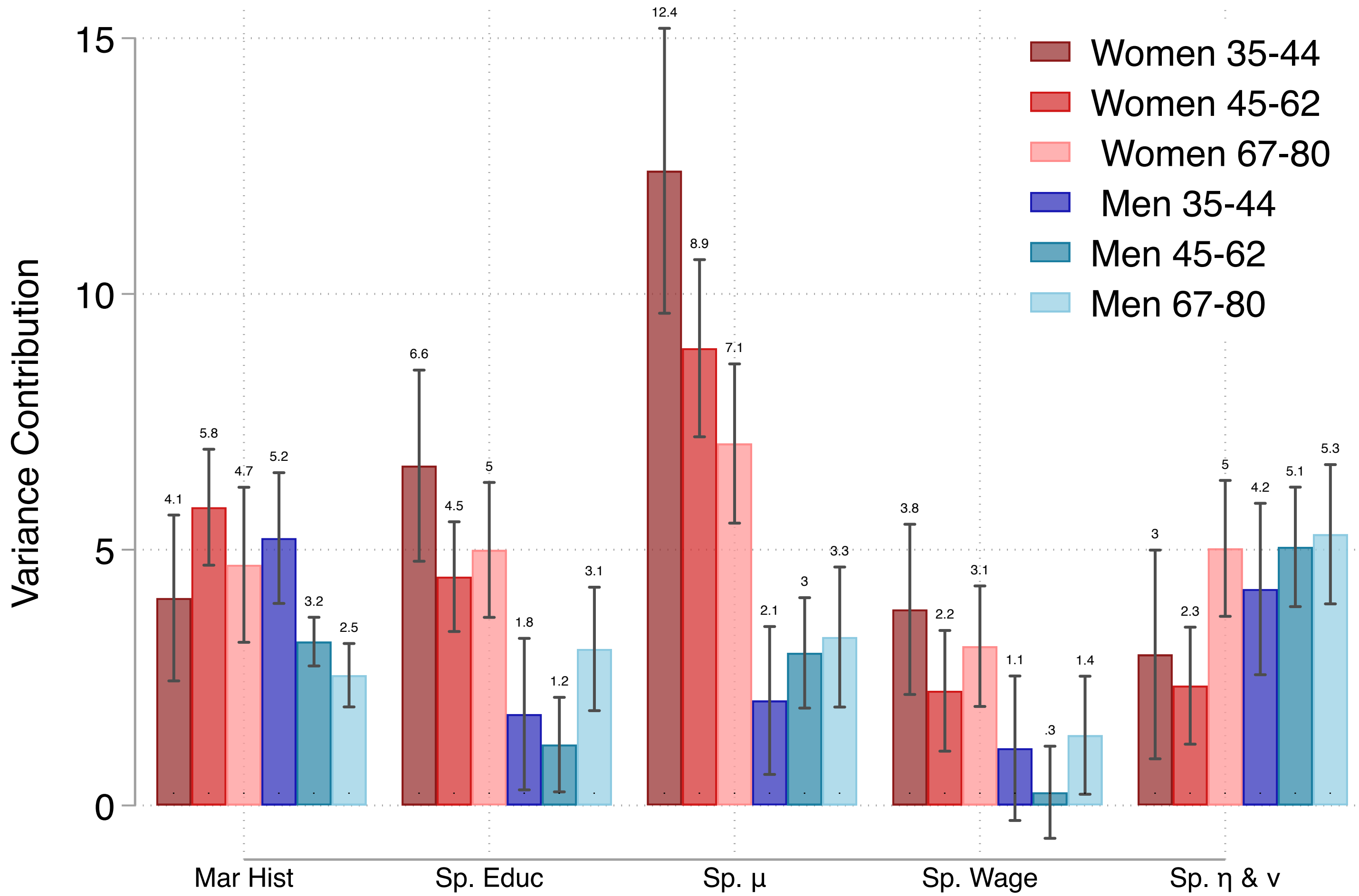
Figure 9 displays the difference in average earnings and log family income per adult equivalent experienced by women and men, at each age, imposing that all individuals have a 1 SD higher permanent wage component throughout their lives, compared to that drawn in the baseline simulation. To obtain the estimates, we first simulate the lives of 500 copies per PSID sample member according to the model estimates. Then, we repeat the procedure, except imposing that all simulated individuals have a 1 SD higher permanent wage component. We display the per-age difference between these two simulations in the average value of each variable. 90% confidence bands are obtained by performing 500 bootstrap simulations.

Figure 10: Contribution of Own Characteristics to the Lifetime Variance of Family Income Per Adult Equivalent



Estimates are based on the simulation of 100 lives per PSID sample member. 90% confidence bands are displayed. Bootstrap standard errors are based on 500 draws of the estimation sample. The bars report, by gender and birth cohort, the percentage of the lifetime variance in log family income per adult equivalent explained by variation in the following factors: (1) education, (2) the permanent wage component μ, (3) the permanent employment component ν and hours component η, (4) the initial draw and shocks to the autoregressive wage component and the i.i.d. wage shocks, (5) the initial draw and the shocks to the autoregressive hours component and the i.i.d. hours shocks, and (6) the i.i.d. shocks to employment status plus variation in initial employment conditional on number of children, marital status, and education. Section 6 discusses the methodology.

Figure 11: Contribution of Spouse Characteristics to the Variance of Lifetime Family Income Per Adult Equivalent



Estimates are based on the simulation of 100 lives per PSID sample member. 90% confidence bands are displayed. Boostrap standard errors are based on 500 draws of the estimation sample. The bars report, by gender and birth cohort, the percentage of the lifetime variance in log family income per adult equivalent explained by variation the following factors: (1) the contribution of random variation in marriage histories conditional on $[\mu, \eta, \nu, \omega_{25}, EDUC]$, (2) the random component ε^{ED_s} of spouse's education, (3) the random component $\tilde{\mu}_s$ of μ_s, (4) the random component of the spouse autoregressive wage component and shocks to wage over the marriage, and (5) ν_s and η_s. Section 6 discusses the methodology.

Earnings, Marriage, and Lifetime Family Income: Generational Change for Men and Women

Online Appendix

Joseph G. Altonji, Daniel Giraldo-Páez, Disa Hynsjo, 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. As a result, because our variable creation and sample selection largely follow that of AGHV, we draw heavily, in some parts verbatim, from that paper's data description and appendix. Appendix Tables A.1a-A.1c provide summary statistics for the PSID sample by cohorts.

Appendix A.1 Sample Selection

Our study uses the 1969-2019 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. Spouses entered the PSID by marrying into a PSID household and are not sample members. We restrict the analysis to the stratified random sample (SRC) and exclude Black sample members, who are underrepresented in the SRC sample.

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 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 ($EARN_{it}$) are 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 this 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.

Hours ($HOURS_{it}^*$) 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.

The measured hourly wage ($WAGE_{it}^*$) is calculated by dividing annual earnings by annual hours ($EARN_{it}^*/HOURS_{it}^*$). As a result, this measure is unavailable when earnings are missing, hours are zero or missing, or in the calendar years 1997 and 1999. Whenever it is missing, we impute the log hourly wage rate $wage_{it}^*$ in one of two ways. First, we fill it using $wage_{2it}^*$, which is the prediction from a regression of $ln\,(EARN_{it}^*/HOURS_{it}^*)$ on log reported hourly wage rate at the time of the survey, $EDUC_i$, and other explanatory variables, fully interacted with gender.[38] 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 $ln\,(EARN_{it}^*/HOURS_{it}^*)$ on the explanatory variables only. Wages are real wages and are in 2012 dollars.

Once we have constructed the hourly wage variable, we censor the wages, hours, and earnings variables. Annual hours are censored from above at 4000 and from below at 200, including when hours are zero. Wages w_{it}^* are censored from below at the minimum federal wage in 1991, \$4.25, corrected for inflation. If w_{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%. Real annual earnings are set to \$1300 in 2012 dollars if they are below \$1300. Similarly to wages, we do not allow increases of more than 500% or decreases of more than 80%.

[38]The PSID asks individuals who are employed at the time of the survey for their current wage rate in their job.

Appendix A.4 Employment Status

Employment (E_{it}), unemployment (U_{it}), and out of the labor force (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. 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. The only exception is that spouses (so married women) were not asked questions about hours of unemployment in the previous year until 1975. 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 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, 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.[39] 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.

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

Table A.1a: Summary Statistics by Gender (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: Summary Statistics by Gender (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 $\vert Earnings/Hours$	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 $\vert Married$	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 $\vert Married$	39.84	10.23	43.04	10.40
Spouse Education $\vert Married$	13.66	2.007	13.64	2.289
Spouse Potential Experience $\vert Married$	20.23	10.13	23.38	10.46
Spouse Log Reported Wage $\vert Married$	2.730	0.500	3.069	0.488
Spouse Wages $\vert Married$	2.901	0.563	3.119	0.584
Spouse Wages $\vert Earnings/Hours, Married$	2.803	0.595	3.160	0.605
Spouse Log Earnings $\vert Married$	9.222	1.488	10.55	1.129
Spouse Log Hours $\vert Married$	6.760	1.008	7.519	0.685
Spouse Employed $\vert Married$	0.725	0.446	0.919	0.273
Spouse Unemployed $\vert Married$	0.017	0.129	0.023	0.150
Spouse Nonparticipation $\vert Married$	0.256	0.437	0.057	0.231

Table A.1c: Summary Statistics by Gender (Cohort 67-80)

	Men		Women	
	Mean	Sd	Mean	Sd
Age	34.95	6.419	34.78	6.323
Education	13.68	2.020	14.05	1.968
Potential Experience	15.27	6.715	14.73	6.598
Log Reported Wage	3.003	0.465	2.861	0.488
Wage $(wage^*)$	3.089	0.584	2.855	0.547
Wage $\|Earnings/Hours$	3.096	0.610	2.884	0.591
Log Hours	7.532	0.674	7.034	0.945
Log Earnings	10.51	1.169	9.715	1.424
Employed	0.910	0.286	0.778	0.414
Unemployed	0.035	0.187	0.037	0.187
Nonparticipation	0.052	0.224	0.182	0.386
Married	0.708	0.453	0.685	0.463
Marriage Duration $\|Married$	6.047	6.370	6.295	6.695
Children Aged 0-5	0.379	0.637	0.374	0.629
Children Aged 6-12	0.488	0.762	0.596	0.808
Children Aged 13-18	0.194	0.490	0.284	0.582
Log Unearned Income	7.289	1.450	7.433	1.506
Log Family Income	11.06	0.834	10.99	0.856
Log Family Income AE	10.43	0.794	10.31	0.837
Level of Family Income	86159	69784	80986	65673
Level of Family Income AE	45141	39012	40447	31968
Log Family Transfers	6.869	1.172	7.085	1.312
Spouse Age $\|Married$	34.18	7.022	37.07	7.138
Spouse Education $\|Married$	14.17	1.965	13.85	2.088
Spouse Potential Experience $\|Married$	14.04	7.091	17.27	7.401
Spouse Log Reported Wage $\|Married$	2.832	0.488	3.065	0.467
Spouse Wages $\|Married$	2.960	0.545	3.111	0.577
Spouse Wages $\|Earnings/Hours, Married$	2.913	0.592	3.151	0.595
Spouse Log Earnings $\|Married$	9.590	1.485	10.57	1.148
Spouse Log Hours $\|Married$	6.921	0.995	7.546	0.646
Spouse Employed $\|Married$	0.768	0.421	0.925	0.263
Spouse Unemployed $\|Married$	0.023	0.150	0.025	0.156
Spouse Nonparticipation $\|Married$	0.207	0.405	0.048	0.215

Appendix B Model Estimates

In this section, we display the full estimates of the model. We also give more detail on some of the estimation procedures. We often follow AGHV verbatim, including the text here for ease of reference.

B.1 The sample used to estimate the distribution of employment, marriage, and number of children at age 25

We use only one observation per person. 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). In estimating the age distribution of children we prioritize the observation at age 25 in a similar fashion. Because the PSID starts in 1968, employment at age 25 is not observed for the 1931–1941 cohort. We extrapolate from the 1945-1962 cohorts. The PSID reports information on age of first marriage and age of each child. Assuming that education is constant, the data allows us to construct a dataset including information on marital status, marriage duration, number of children, and education at age 25, for individuals in the early cohorts. We use this dataset to impute employment status that is predicted using the same variables, but with individuals from later cohorts.

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

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

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_{it-1}, is excluded.

Define $e_{it}^w = \mu_i + \omega_{it} + \varepsilon_{it}^w + me_{it}^w$. Using (4) for men,

$$e_{it}^w - \gamma_U^\omega U_{i,t-1} = \rho^\omega e_{it-1}^w + (1-\rho^\omega)\mu_i + u_{it}^\omega + (\varepsilon_{it}^w + me_{it}^w) - \rho^\omega\left(\varepsilon_{it}^w + me_{t-1}^w\right). \tag{7}$$

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 $(e_{it-2}^w - e_{it-3}^w)$ and $(e_{it-3}^w - e_{it-4}^w)$. Define the quasi difference qe_{it}^w as

$$\begin{aligned} qe^w_{it} &\equiv e^w_{it} - \gamma^\omega_U U_{i,t-1} - \rho^\omega e^w_{it-1} & (8) \\ &= (1-\rho^\omega)\mu_i + u^\omega_{it} + (\varepsilon^w_{it} + me^w_{it}) - \rho^\omega \left(\varepsilon^w_{it} + me^w_{it-1}\right), & (9) \end{aligned}$$

where the second equation follows from (4).

Because u_{it}, ε^w_{it}, and me^w_{it} are serially uncorrelated, $Cov(qe^w_{it}, e^w_{it-k}) = (1-\rho)\sigma^2_{\mu^w}$ for any $k = 2, 3, ...$ We average over values for $k = 2$ to 6, so the moment condition is

$$\sigma^2_{\mu^w} = \frac{1}{5(1-\rho)} \sum_{k=2}^{6} cov(qe^w_{it}, e_{it-k}).$$

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

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

$$wage^{**}_{it} = X^w_{it}\gamma^w_X + Mar_{it}\gamma^w_{mar} + \mu_i + \omega_{it} + \varepsilon^{w**}_{it} + me^{w**}_{it}.$$

We assume that me^{w**}_{it} and me^w_{it} 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 $\varepsilon^w_{it} = \varepsilon^{w**}_{it}$ and that ω_{it} and ε^w_{it} are covariance stationary.

Consider the regression of $wage^*_{it}$ on $wage^*_{it-1}$. 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 $wage^{**}_{it-1}$ as the instrument for $wage^*_{it-1}$. Then it can be shown that

$$var\left(me^w_{it}\right) = \left(1 - \frac{b_{1OLS}}{b_{1IV}}\right) var\left(wage^*_{it}\right).$$

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

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

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

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

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

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

$$var(\mu_i) + var(\omega_{it}) + var(me_{it}) + var(\varepsilon^w_{it})$$

to estimate $var(\varepsilon^w_{it})$.

The procedure is the same for women, except that the model of $wage^*_{it}$ includes lags of E_{it} and U_{it}, and 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 σ_{ε^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^h_{me} (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^2_η. 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^2_η is at least 0.004.

B.4 Estimation of Sorting Parameters for Wage Error Components

Following AGHV, we use the method of moments to fit $\gamma^{\mu_s}_{m\mu}$ and $\gamma^{\omega_s}_{m\omega}$ to the covariances of the wage residuals of the sample member and the spouse at various leads and lags during the marriage. We allow all parameters to depend on whether $B_i \leq 1962$. Consider the case of male sample members. Let $wres^*_{it}$ and $wres^{s*}_{it}$ denote the composite error term for the male and female specifications of (1):

$$wres^*_{it} \equiv \mu_i + \omega_{it} + \varepsilon^w_{it} + me^w_{it}$$

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

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

$$cov(wres_{i,t_0(i)+j-1}^*, wres_{i,t_0(i)+k}^{s*}) = (\gamma_{m\mu}^{w^s})Var(\mu_{mi}) + \gamma_{m\omega}^{w^s}(\rho_m^\omega)^{j+1}(\rho_f^\omega)^{k-1}Var(\omega_{mit_0-1}), \quad (10)$$

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 $Var(\mu_{mi})$, $Var(me_{it}^w)$, and Var (ε_{it}^w). We obtain ρ_m^ω and ρ_f^ω from the estimation of the wage equation. We replace $cov(wres_{i,t_0(i)+j-1}^*, wres_{si,t_0(i)+k}^*)$ in (10) with sample estimates and estimate $\gamma_{m\mu}^{\mu^s}$ and $\gamma_{m\omega}^{\omega^s}$ 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 $wres_{it}^{s*}$ 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_{me}^h to 0.122. For men, this implies that measurement error accounts for 12% of the variance of $hour_{it}^*$ when $hour_{it}^*$ exceeds the floor of ln(200). For women the value is 6%. Reducing (increasing) the value of σ_{me}^h 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 the impulse response functions that we report. (For how we set σ_{me}^w, see Appendix B.2.)

Table B.1a: Log Wage Model

	(1) Men	(2) Women
Married	0.050***	-0.005
	(0.010)	(0.016)
Education	0.135***	0.134***
	(0.005)	(0.005)
Potential Experience	0.016***	0.012***
	(0.001)	(0.001)
Potential Experience^2	-0.001***	-0.001***
	(0.000)	(0.000)
Potential Experience^3	0.000***	0.000***
	(0.000)	(0.000)
Education*Potential Experience	0.001***	0.000
	(0.000)	(0.000)
Education*Potential Experience^2	-0.000***	-0.000***
	(0.000)	(0.000)
Year	0.003***	0.005***
	(0.001)	(0.001)
Year^2	0.000***	0.000***
	(0.000)	(0.000)
Year^3	-0.000***	-0.000***
	(0.000)	(0.000)
Cohort*Married		0.002**
		(0.001)
Cohort^2*Married		0.000
		(0.000)
Lag Participation		0.137***
		(0.012)
Lag Unemployed		-0.080***
		(0.009)
Second Lag Participation		0.093***
		(0.011)
Second Lag Unemployed		-0.075***
		(0.008)
Third Lag Participation		0.060***
		(0.011)
Female*Children 0-5		0.005
		(0.013)
Female*Children 6-12		-0.055***
		(0.010)
Female*Children 13-18		-0.059***
		(0.012)
Cohort*Female*Children 0-5		0.003***
		(0.001)

Cohort*Female*Children 6-12		-0.000
		(0.001)
Cohort*Female*Children 13-18		-0.000
		(0.001)
Cohort^2*Female*Children 0-5		-0.000***
		(0.000)
Cohort^2*Female*Children 6-12		-0.000*
		(0.000)
Cohort^2*Female*Children 13-18		-0.000*
		(0.000)
Cohort^2		-0.000
		(0.000)
Constant	2.962***	2.456***
	(0.015)	(0.027)
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 for women 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.

B.2: Labor Market Status Multinomial Logit Estimates

	Men		Women	
	Unemployed	Employed	Unemployed	Employed
Education	0.081**	0.234***	0.243***	0.347***
	(0.040)	(0.039)	(0.042)	(0.039)
Married	0.343***	0.819***	-1.017***	-0.206
	(0.102)	(0.097)	(0.191)	(0.161)
Children Aged 0-5	-0.087	-0.109	-0.875***	-0.947***
	(0.094)	(0.091)	(0.117)	(0.107)
Children Aged 6-12	-0.101	-0.098	-0.300***	-0.429***
	(0.068)	(0.065)	(0.075)	(0.070)
Children Aged 13-18	0.056	0.083	-0.101	-0.291***
	(0.085)	(0.079)	(0.086)	(0.079)
Married*Children 0-5			-0.119	0.047
			(0.128)	(0.113)
Married*Children 6-12			0.018	0.133*
			(0.085)	(0.076)
Married*Children 13-18			0.112	0.220**
			(0.100)	(0.088)
Potential Experience	0.009	-0.000	-0.028*	-0.018
	(0.014)	(0.013)	(0.015)	(0.014)
Potential Experience^2	-0.004***	-0.004***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Potential Experience^3	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Married*Education			-0.179***	-0.173***
			(0.037)	(0.033)
Married*Potential Experience			0.014	0.022
			(0.018)	(0.016)
Married*Potential Experience^2			-0.000	0.000
			(0.001)	(0.001)
Married*Potential Experience^3			-0.000	-0.000
			(0.000)	(0.000)
Year	-0.115***	-0.070***	-0.038***	-0.011
	(0.013)	(0.012)	(0.015)	(0.013)
Year^2	0.001**	0.001*	-0.000	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Married*Year^2			-0.001**	-0.001*
			(0.001)	(0.000)
Cohort*Education	0.012***	0.009**	0.004	0.007**
	(0.004)	(0.004)	(0.003)	(0.003)
Cohort^2*Education	0.000*	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Cohort^3*Education	-0.000**	-0.000*	-0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)
Cohort*Children 0-5	0.002	0.002		
	(0.006)	(0.006)		
Cohort*Children 6-12	-0.008*	-0.010**		
	(0.005)	(0.005)		
Cohort*Children 13-18	-0.003	-0.003		
	(0.007)	(0.006)		
Year^3	0.000***	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Lag Unemployed	0.410***	-1.850***	0.593***	-1.102***
	(0.106)	(0.103)	(0.133)	(0.125)
Lag Participation	2.016***	4.654***	1.542***	3.469***
	(0.108)	(0.099)	(0.119)	(0.103)
Cohort^2	-0.001	-0.000	0.000	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Cohort^3	0.000***	0.000	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Cohort*Married			0.011	0.015
			(0.011)	(0.010)
Cohort^2*Married			-0.001	-0.001***
			(0.000)	(0.000)
Cohort*Potential Experience			-0.001	0.002*
			(0.002)	(0.001)
Cohort*Potential Experience^2			0.000*	0.000*
			(0.000)	(0.000)
Cohort*Potential Experience^3			0.000***	0.000***
			(0.000)	(0.000)
Married*Year^3			0.000**	0.000***
			(0.000)	(0.000)
Married*Lag Paricipation			0.145	-0.258**
			(0.139)	(0.113)
Married*Lag Unemployed			0.856***	0.486***
			(0.165)	(0.153)
Constant	1.110***	0.582***	0.243	0.773***
	(0.193)	(0.187)	(0.195)	(0.177)
σ_v	1.790		1.800	
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 normally distributed unobserved heterogeneity. 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. Simulations reveal that unconstrained estimates imply lower persistence in employment compared to the data, especially at long lags. To correct for this, we re-estimate the labor market status model while constraining the variance of unobserved heterogeneity to be equal to twice the size of the unconstrained estimate. We do this for both men and women. Since this parameter is constrained to a specific value in the estimation, there is no standard error. The standard errors on the unconstrained estimates (which are 1.60 for men and 1.62 for women) are 0.200 and 0.106 for men and women, respectively. 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 B.3a: Log Hours Model

	Men	Women
Wage	0.089***	0.244***
	(0.012)	(0.016)
Married	0.015**	0.487***
	(0.008)	(0.064)
Education	0.010**	-0.006
	(0.004)	(0.009)
Female*Children 0-5		-0.152***
		(0.023)
Female*Children 6-12		-0.098***
		(0.015)
Female*Children 13-18		-0.025*
		(0.014)
Married*Children 0-5		-0.108***
		(0.023)
Married*Children 6-12		-0.033**
		(0.015)
Married*Children 13-18		0.009
		(0.015)
Cohort*Wage	0.003***	0.002
	(0.001)	(0.001)
Potential Experience	0.008***	-0.039**
	(0.002)	(0.016)
Potential Experience^2	0.000	0.003**
	(0.000)	(0.001)
Potential Experience^3	-0.000**	0.000
	(0.000)	(0.000)
Year	-0.011***	0.032**
	(0.002)	(0.016)
Year^2	-0.000	-0.003**
	(0.000)	(0.001)
Year^3	0.000	0.000**
	(0.000)	(0.000)
Unemployed	-0.474***	-0.360***
	(0.016)	(0.022)
Cohort*Unemployed	-0.005***	-0.005***
	(0.001)	(0.001)
Cohort^2*Unemployed	0.000***	0.000
	(0.000)	(0.000)
Cohort^2	0.000	0.003**
	(0.000)	(0.001)
Education*Potential Experience	0.001***	
	(0.000)	
Potential Experience^2*Education	-0.000***	

	(0.000)	
Log Spouse Predicted Wage $\|Married$		-0.193***
		(0.019)
Married*Unemployed Spouse		0.027*
		(0.015)
Married*Unemployed		0.042*
		(0.024)
Married*Education		0.010
		(0.008)
Married*Potential Experience		0.000
		(0.002)
Married*Potential Experience^2		-0.000
		(0.000)
Married*Year		0.008***
		(0.001)
Married*Year^2		-0.000**
		(0.000)
Cohort*Female*Children 0-5		0.002**
		(0.001)
Cohort*Female*Children 6-12		0.002***
		(0.001)
Cohort*Female*Children 13-18		0.001*
		(0.001)
Cohort*Education		0.007***
		(0.003)
Cohort^2*Education		0.000
		(0.000)
Cohort*Potential Experience		0.007**
		(0.003)
Cohort*Potential Experience^2		0.000
		(0.000)
Cohort*Potential Experience^3		0.000
		(0.000)
Potential Experience*Education		0.007***
		(0.003)
Constant	7.489***	6.680***
	(0.037)	(0.115)
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***
R-squared	1.00	1.00
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 (in parentheses) 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 $\sigma_{me^h}$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	-0.262***		
	(0.046)		
Female Wage	0.055		
	(0.042)		
Education*Male	0.041***		
	(0.012)		
Education*Female	0.000		
	(0.014)		
Male Log Hours	-0.515***		
	(0.041)		
Female Log Hours	-0.091***		
	(0.020)		
Age*Male	0.019***		
	(0.007)		
Age*Female	0.031***		
	(0.010)		
Year	-0.010***	-0.004	-0.002
	(0.003)	(0.004)	(0.004)
Year^2	-0.000***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)
Year^3	0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Children Aged 0-5	-0.043*	-0.047	
	(0.025)	(0.066)	
Children Aged 6-12	-0.017		
	(0.032)		
Log Hours		-0.455***	-0.513***
		(0.047)	(0.040)
Wage		-0.033	-0.107*
		(0.050)	(0.059)
Education		0.016	0.056***
		(0.014)	(0.015)
Age		0.028*	0.036**
		(0.015)	(0.015)
Female*Children 0-5			0.331***
			(0.048)
Female*Children 6-12			0.348***
			(0.054)
Constant	12.670***	10.842***	11.272***
	(0.387)	(0.410)	(0.391)
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 model 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. 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					-0.342***		
					(0.026)		
Female Wage					0.121***		
					(0.025)		
Education*Male					0.060***		
					(0.010)		
Education*Female					0.059***		
					(0.011)		
Male Log Hours					-0.540***		
					(0.021)		
Female Log Hours					-0.169***		
					(0.015)		
Log Hours	-0.599***	-0.582***	-0.499***	-0.256***		-0.683***	-0.421***
	(0.033)	(0.029)	(0.069)	(0.053)		(0.074)	(0.054)
Wage	0.062	-0.092*	-0.093	0.239***		-0.023	0.100
	(0.051)	(0.048)	(0.076)	(0.092)		(0.096)	(0.099)
Education	0.079***	0.086***	0.031	0.068***		0.102***	0.065***
	(0.016)	(0.015)	(0.020)	(0.023)		(0.025)	(0.025)
Age	0.024***	0.040***	0.052***	0.031***		0.032***	0.009
	(0.005)	(0.004)	(0.009)	(0.010)		(0.011)	(0.009)
Age^2	-0.000	-0.001	0.000	-0.003**		0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
Age^3	0.000	0.000	-0.000	0.000*		0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Year	-0.011**	-0.000	-0.011	-0.017**	-0.012***	-0.016*	-0.028***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.002)	(0.008)	(0.008)
Year^2	-0.001***	-0.000	-0.001**	-0.001**	-0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year^3	0.000	-0.000**	0.000	0.000	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Children Aged 0-5	0.167*		-0.019		-0.068***	0.284***	
	(0.092)		(0.084)		(0.017)	(0.093)	
Female*Children 0-5		0.237***		0.173**			0.345***
		(0.055)		(0.080)			(0.076)
Female*Children 6-12		0.407***		0.288***			0.339***
		(0.032)		(0.059)			(0.062)
Female*Children 13-18		0.472***		0.224***			0.323***
		(0.038)		(0.081)			(0.078)
Age*Male					0.027***		
					(0.004)		
Age^2*Male					-0.000		
					(0.000)		
Age^3*Male					0.000**		
					(0.000)		
Age*Female					0.008**		
					(0.004)		
Age^2*Female					-0.001***		
					(0.000)		
Age^3*Female					0.000***		
					(0.000)		
Children Aged 6-12					-0.036**		
					(0.015)		
Children Aged 13-18					-0.007	0.117	
					(0.018)	(0.091)	
Constant	11.512***	11.698***	11.719***	8.873***	13.415***	12.376***	10.358***
	(0.284)	(0.259)	(0.580)	(0.468)	(0.211)	(0.622)	(0.473)
ρ	0.550	0.634	0.464	0.478	0.620	0.483	0.294
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 estimates using ordinary least squares including individuals aged 25 and over. 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. See Section 3.3. See also the notes to Table B.1a for the variable normalizations.

Table B.5: Single to Married Transitions Probit Model

	Single to Married
Female	0.037
	(0.181)
Education	-0.024***
	(0.009)
Education*Female	0.024*
	(0.012)
Lag Wage	0.111***
	(0.029)
Lag Log Wages*Female	-0.091**
	(0.042)
Lag Participation	0.263***
	(0.071)
Lag Participation*Female	-0.273***
	(0.089)
Lag Unemployed	-0.089**
	(0.044)
Lag Unemployed*Female	0.141**
	(0.062)
Lag Index for Young Children	0.393***
	(0.062)
Cohort*Education	0.001*
	(0.001)
Cohort*Education*Female	-0.000
	(0.001)
Lag Age	-0.016
	(0.010)
Lag Age^2	-0.000
	(0.000)
Lag Age*Female	0.004
	(0.003)
Lag Age^2*Female	-0.000
	(0.000)
Year	-0.017*
	(0.010)
Year^2	-0.000***
	(0.000)
Year^3	0.000***
	(0.000)
Cohort*Female	0.014
	(0.011)
Cohort^2	-0.000
	(0.000)
Cohort*Lag Index for Young Children	-0.018***
	(0.005)
Cohort^2*Lag Index for Young Children	0.001***
	(0.000)
Constant	-1.325***
	(0.181)
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 equation. 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 years 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	0.396***
	(0.040)
Lag Education*Male	0.046***
	(0.011)
Lag Education*Female	0.056***
	(0.013)
Female	-0.150***
	(0.030)
Absolute Difference Male - Female Education	-0.031***
	(0.010)
Absolute Difference Male - Female Age	-0.018***
	(0.004)
Lag Age*Male	0.005
	(0.005)
Lag Age*Female	0.012**
	(0.005)
Lag Age^2*Male	0.000
	(0.000)
Lag Age^2*Female	-0.000
	(0.000)
Lag Age^3*Male	-0.000
	(0.000)
Lag Age^3*Female	0.000
	(0.000)
Lag Marriage Duration	0.135*
	(0.070)
Lag Marriage $Duration^2$	-0.002
	(0.001)
Lag Marriage $Duration^{1/2}$	-0.553**
	(0.278)
Year	0.009
	(0.018)
$Year^2$	-0.002*
	(0.001)
$Year^3$	-0.000***
	(0.000)
Lag Log Wages*Male	0.138***
	(0.032)
Lag Log Wages*Female	-0.004
	(0.034)
Second Lag Participation*Male	0.377***
	(0.053)
Second Lag Participation*Female	-0.024

	(0.030)
Second Lag Unemployed*Male	-0.095***
	(0.037)
Second Lag Unemployed*Female	-0.107***
	(0.041)
Absolute Difference Male - Female Wages	0.063*
	(0.038)
Cohort^2	0.000*
	(0.000)
Cohort*Lag Education*Male	0.002***
	(0.001)
Cohort*Lag Education*Female	0.002***
	(0.001)
Cohort^2*Lag Education*Male	-0.000
	(0.000)
Cohort^2*Lag Education*Female	-0.000**
	(0.000)
Cohort*Absolute Difference Male - Female Education	-0.001
	(0.001)
Cohort*Second Lag Participation*Male	0.007**
	(0.003)
Cohort*Second Lag Participation*Female	0.000
	(0.002)
Cohort*Lag Marriage Duration	0.002
	(0.002)
Cohort*Lag Marriage Duration^2	-0.000
	(0.000)
Cohort*Lag Marriage Duration$^{1/2}$	-0.009
	(0.006)
Year*Lag Marriage Duration	0.000
	(0.004)
Year*Lag Marriage Duration^2	-0.000
	(0.000)
Year*Lag Marriage Duration$^{1/2}$	-0.003
	(0.016)
Year^2*Lag Marriage Duration	-0.000
	(0.000)
Year^2*Lag Marriage Duration^2	0.000
	(0.000)
Year^2*Lag Marriage Duration$^{1/2}$	0.002
	(0.001)
Constant	1.676***
	(0.325)
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. Beause 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	0.586***	0.508***	0.623***	0.544***
	(0.029)	(0.028)	(0.034)	(0.033)
Children Aged 0-5	-0.369***		-0.100**	
	(0.043)		(0.044)	
Lag of Children Aged 0-5		-0.248**		-0.382***
		(0.117)		(0.106)
Lag of Children Aged 6-12		-0.125*		-0.243***
		(0.070)		(0.071)
Lag of Children Aged 13-18		-0.055		-0.160
		(0.117)		(0.104)
Age	0.050***	-0.021*	0.039***	-0.007
	(0.013)	(0.011)	(0.010)	(0.013)
Age^2		-0.002*		-0.001
		(0.001)		(0.001)
Age^3		0.000		0.000
		(0.000)		(0.000)
Year	0.019***	0.021***	-0.007**	0.001
	(0.003)	(0.005)	(0.003)	(0.005)
$Year^2$	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year*Education	0.000		-0.004***	
	(0.001)		(0.001)	
$Year^2$*Education	-0.000		0.000**	
	(0.000)		(0.000)	
$Cohort^2$		-0.000		-0.000
		(0.000)		(0.000)
Cohort*Education		0.003*		-0.002
		(0.002)		(0.002)
$Cohort^2$*Education		-0.000		0.000
		(0.000)		(0.000)
Constant	1.276***	1.191***	0.794***	1.015***
	(0.139)	(0.110)	(0.125)	(0.131)
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 Age

	Male Sample Member		Female Sample Member	
	Age 25	After Age 25	Age 25	After Age 25
Education	0.024	0.042	-0.309***	-0.077
	(0.035)	(0.073)	(0.047)	(0.084)
Children Aged 0-5	-0.187**		0.029	
	(0.077)		(0.103)	
Lag of Children Aged 0-5		-1.239***		0.040
		(0.272)		(0.302)
Lag of Children Aged 6-12		0.322		0.381
		(0.237)		(0.251)
Lag of Children Aged 13-18		0.982***		-0.132
		(0.337)		(0.393)
Age	0.809***	0.780***	0.954***	0.899***
	(0.025)	(0.038)	(0.025)	(0.043)
Age^2		0.001		0.002
		(0.004)		(0.004)
Age^3		0.000		-0.000
		(0.000)		(0.000)
Year	0.030***	0.052***	0.012**	-0.013
	(0.005)	(0.014)	(0.006)	(0.016)
$Year^2$	-0.001	0.000	-0.001**	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
$Cohort^2$		-0.004***		0.002**
		(0.001)		(0.001)
$Cohort^2$*Age		-0.000***		0.000
		(0.000)		(0.000)
Constant	-1.973***	-2.356***	3.046***	1.596***
	(0.263)	(0.345)	(0.282)	(0.387)
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 simulated 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 Employment

	Spouse Employment Status	
	Spouse Unemployed	Spouse Employed
Education	0.003	0.109***
	(0.046)	(0.035)
Lag Wage	0.148	-0.011
	(0.154)	(0.122)
Potential Experience	-0.025	-0.003
	(0.023)	(0.016)
Potential Experience^2	-0.001	-0.001
	(0.001)	(0.001)
Potential Experience^3	-0.000	0.000
	(0.000)	(0.000)
Lag Children Aged 0-5	-0.489**	-0.426***
	(0.196)	(0.138)
Lag Children Aged 6-12	-0.002	-0.041
	(0.130)	(0.098)
Lag Children Aged 13-18	0.280	-0.049
	(0.178)	(0.153)
Lag Participation	-0.109	0.753***
	(0.318)	(0.277)
Lag Unemployed	-0.449**	-0.742***
	(0.215)	(0.168)
Year	-0.009	0.011*
	(0.007)	(0.006)
Year^2	0.000	-0.001*
	(0.001)	(0.000)
Constant	-0.563	0.951**
	(0.586)	(0.475)
Observations	1439	

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

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 on 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 Employment

	Spouse Employment Status	
	Spouse Unemployed	Spouse Employed
Education	0.013	0.098*
	(0.061)	(0.057)
Lag Wage	0.269	0.362
	(0.251)	(0.239)
Potential Experience	-0.010	-0.016
	(0.016)	(0.015)
Potential Experience^2	-0.001	-0.002
	(0.001)	(0.001)
Lag Children Aged 0-5	-0.075	-0.030
	(0.190)	(0.174)
Lag Children Aged 6-12	0.163	-0.079
	(0.139)	(0.129)
Lag Children Aged 13-18	0.122	0.119
	(0.182)	(0.167)
Lag Participation	0.458*	0.730***
	(0.259)	(0.238)
Lag Unemployed	-0.010	-0.398*
	(0.260)	(0.236)
Year	-0.032***	-0.006
	(0.010)	(0.010)
Year^2	0.000	-0.000
	(0.001)	(0.001)
Constant	-0.360	0.734
	(0.787)	(0.752)
Observations	1444	

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

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. That is, the estimation of these models do not include instances in which wage is predicted using only demographics. The model is estimated on 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.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 3.5.2 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 3.5.2). 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	0.062***	-0.066**	0.091***	-0.061***
	(0.007)	(0.026)	(0.008)	(0.022)
Lag Children Aged 0-5	-0.002	0.180**	-0.043***	0.179***
	(0.015)	(0.078)	(0.015)	(0.051)
Lag Children Aged 6-12	-0.240***	0.046	-0.254***	0.074*
	(0.016)	(0.057)	(0.016)	(0.038)
Lag Children Aged 13-18	-0.243***	0.065	-0.304***	-0.127*
	(0.035)	(0.098)	(0.036)	(0.076)
Lag Age	-0.015***	-0.047**	-0.068***	-0.074***
	(0.005)	(0.018)	(0.006)	(0.016)
Lag Age^2	-0.002***	-0.003**	-0.006***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.002)
Lag Age^3	0.000*	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year	0.008***	0.006	0.006***	0.007**
	(0.002)	(0.005)	(0.002)	(0.003)
Year^2	0.000***	-0.001*	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cohort*Education	0.000	-0.003	0.001*	0.001
	(0.000)	(0.002)	(0.000)	(0.001)
Cohort^2*Education	-0.000***	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Spouse Age	-0.072***		-0.017***	
	(0.004)		(0.003)	
Spouse Age^2	-0.003***		-0.001***	
	(0.000)		(0.000)	
Year^3	-0.000**		-0.000**	
	(0.000)		(0.000)	
Cohort^2	-0.000**	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.293***	-2.223***	-1.299***	-2.174***
	(0.030)	(0.086)	(0.036)	(0.081)
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

We simulate 500 lives for each member of the PSID sample to evaluate fit. The procedure is described in Section 4.

As discussed in the main text, our model fits the data reasonably well overall, but, not surprisingly, 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. The structure of this section follows that of the Model Fit appendix of AGHV; we review the same patterns in the data, this time with an eye towards cohort-specific 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

For men and women separately, Tables C.1a-C.1c and Figures C.1-C.4 show that the model fits the PSID data fairly well for the overall mean, standard deviation, and age profiles of labor force status, hourly wages, hours worked, and earnings. A few exceptions, which we discuss in the main text of the paper, include the following: For young women in the 1935–44 cohort, the model understates employment and overstates nonparticipation somewhat (Table C.1a and Figures C.1-C.2) and understates log wages (Table C.1a and Figure C.3). For the 1945-62 cohort, the model slightly underpredicts hours for women at older ages (Figure C.3).

For all cohort groups, but especially the 1935–44 group, the model somewhat overpredicts earnings for women (Tables C.1a and C.1c, and Figure C.4).

C.1.2 Marriage and Fertility

Tables C.1a-C.1c and Figure C.5 show that the model fits marriage rates and marriage duration fairly well overall. Two exceptions, which we discuss in the paper, are marriage rates at young ages for the 1935-44 cohort group (for both men and women), which the model underpredicts, and marriage rates for older women in the 1967-80 cohort group, which are somewhat overpredicted. The tables and figure also show that the model matches marriage duration (which evolves endogenously in the model) quite well.

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 1935–44 cohort group.

C.1.3 Family income and nonlabor income

Tables C.1a–C.1c and Figure C.7 show that the fit of family income is fairly good overall, though for the 1935-44 cohort group the model somewhat understates family income for women and overstates y_ae for men, especially at young ages. The tables also show that the model somewhat overpredicts the level of nonlabor income 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.1a 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 1935-44 cohort and at old ages in the 1967-80 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 fit is quite good. 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 also 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 1967-80 cohort group, the estimated coefficient is somewhat understated in the simulated data for both men (0.23 versus 0.34 in the PSID data) and women (0.23 versus 0.30 in the PSID).

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. The miss in earnings persistence is primarily driven by an underpredicted persistence in hours (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 (Cohorts 35-44)

	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	3.05	0.65	2.48	0.56	2.47	0.60
Log Hours	7.63	0.52	7.59	0.55	6.62	1.03	6.63	0.99
Employed	0.86	0.35	0.84	0.36	0.67	0.47	0.63	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	0.18	0.25	0.43	0.29	0.45
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	0.60	0.49
Log Earnings	10.64	0.93	10.65	0.97	8.97	1.46	9.11	1.44
Level of Earnings	56176.50	48707.86	60286.52	51971.03	18068.44	19942.85	20870.60	27459.81
Married	0.88	0.33	0.84	0.37	0.83	0.38	0.75	0.43
Marriage Duration | Married	14.00	10.02	13.95	10.36	15.09	11.14	13.74	11.34
$Prob(Married_{t+1}\|Married_t)$	0.98	0.15	0.98	0.15	0.98	0.15	0.98	0.15
$Prob(Single_{t+1}\|Married_t)$	0.14	0.35	0.13	0.34	0.09	0.28	0.07	0.25
Children Aged 0-5	0.25	0.56	0.22	0.52	0.17	0.47	0.17	0.46
Children Aged 6-12	0.59	0.86	0.47	0.77	0.52	0.84	0.44	0.78
Children Aged 13-18	0.46	0.73	0.43	0.72	0.48	0.75	0.45	0.76
Age of Spouse | Married	37.87	8.43	38.63	8.45	44.03	9.04	43.33	8.99
Education of Spouse | Married	12.60	1.93	12.63	2.07	12.90	2.74	13.00	2.50
Log Wage of Spouse | Married	2.49	0.57	2.42	0.59	3.08	0.62	3.10	0.65
Log Hours of Spouse | Married	6.47	1.03	6.50	0.97	7.62	0.56	7.57	0.61
Spouse Employed | Married	0.65	0.48	0.60	0.49	0.88	0.32	0.86	0.35
Spouse Unemployed | Married	0.05	0.23	0.07	0.26	0.09	0.28	0.10	0.29
Spouse Nonparticipation | Married	0.29	0.46	0.32	0.47	0.03	0.18	0.04	0.20
Log earnings of Spouse | Married	8.74	1.42	8.92	1.41	10.63	1.05	10.67	1.03
Log Family Income	11.07	0.63	11.07	0.73	11.03	0.70	10.94	0.84
Level of Family Income	77264.49	51995.27	82009.78	60001.20	77178.46	59042.84	76098.59	60442.85
Log of Unearned Income	7.61	1.63	7.77	1.35	7.83	1.68	7.90	1.38
Level of Unearned Income	8821.67	21452.83	6879.26	15098.72	10320.32	23360.87	7914.50	16696.85
Log Family Income AE	10.29	0.70	.	.	10.29	0.73	.	.
Observations	8890		4445000		9419		4709500	

Table C.1a shows the means 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.

Table C.1b: Comparison of PSID and Simulated Means and Standard Deviations (Cohorts 45-62)

	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	3.09	0.65	2.65	0.62	2.64	0.63
Log Hours	7.57	0.58	7.55	0.61	6.92	0.96	6.88	0.93
Employed	0.86	0.35	0.86	0.35	0.75	0.43	0.73	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	0.20	0.17	0.38	0.20	0.40
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	0.48
Log Earnings	10.59	1.07	10.64	1.04	9.46	1.43	9.53	1.40
Level of Earnings	60395.15	91915.72	62147.03	55162.75	26734.03	30481.76	28588.85	33976.74
Married	0.77	0.42	0.79	0.40	0.73	0.44	0.74	0.44
Marriage Duration | Married	9.59	9.25	10.80	9.56	9.68	9.72	10.63	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	0.55	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	0.76
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	38.47	9.27	41.49	9.47	41.85	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	2.62	0.64	3.08	0.62	3.13	0.66
Log Hours of Spouse | Married	6.76	1.00	6.80	0.94	7.56	0.63	7.55	0.61
Spouse Employed | Married	0.73	0.45	0.72	0.45	0.87	0.33	0.87	0.34
Spouse Unemployed | Married	0.06	0.24	0.06	0.25	0.09	0.28	0.09	0.29
Spouse Nonparticipation | Married	0.21	0.41	0.21	0.41	0.04	0.20	0.04	0.20
Log earnings of Spouse | Married	9.29	1.47	9.43	1.41	10.62	1.09	10.68	1.05
Log Family Income	11.07	0.75	11.15	0.77	10.97	0.80	11.02	0.86
Level of Family Income	82427.58	64496.34	90236.83	67210.98	76674.40	61345.99	83877.32	67266.56
Log of Unearned Income	7.56	1.57	7.74	1.32	7.70	1.60	7.85	1.35
Level of Unearned Income	8096.77	21454.19	6471.90	14244.08	8896.37	22283.92	7343.25	15658.53
Log Family Income AE	10.39	0.75	.	.	10.29	0.79	.	.
Observations	27658		13829000		29574		14787000	

Table C.1b shows the means 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 cohort.

Table C.1c: Comparison of PSID and Simulated Means and Standard Deviations (Cohorts 67-80)

	Men				Women			
	PSID		Simulated		PSID		Simulated	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Age	34.95	6.42	34.95	6.42	34.78	6.32	34.78	6.32
Education	13.69	2.02	13.69	2.02	14.06	1.97	14.06	1.97
Log Wage	3.04	0.64	3.05	0.65	2.73	0.64	2.75	0.65
Log Hours	7.53	0.67	7.50	0.68	7.03	0.95	7.01	0.92
Employed	0.88	0.32	0.87	0.33	0.77	0.42	0.76	0.43
Unemployed	0.07	0.25	0.07	0.25	0.07	0.25	0.07	0.25
Nonparticipation	0.05	0.23	0.06	0.24	0.17	0.37	0.17	0.37
Employed to Unemployed	0.04	0.19	0.04	0.20	0.04	0.20	0.05	0.22
Unemployed to Employed	0.58	0.49	0.63	0.48	0.55	0.50	0.64	0.48
Log Earnings	10.52	1.19	10.55	1.14	9.69	1.45	9.77	1.40
Level of Earnings	58923.97	59230.56	59445.21	54567.29	32916.12	34891.81	35119.20	39410.86
Married	0.71	0.45	0.70	0.46	0.69	0.46	0.70	0.46
Marriage Duration | Married	6.05	6.37	6.78	6.85	6.30	6.69	6.98	6.98
$Prob(Married_{t+1} \mid Married_t)$	0.97	0.17	0.97	0.17	0.97	0.18	0.97	0.18
$Prob(Single_{t+1} \mid Married_t)$	0.12	0.33	0.11	0.31	0.11	0.31	0.11	0.31
Children Aged 0-5	0.38	0.64	0.35	0.63	0.37	0.63	0.38	0.65
Children Aged 6-12	0.49	0.76	0.49	0.76	0.60	0.81	0.59	0.83
Children Aged 13-18	0.19	0.49	0.27	0.59	0.28	0.58	0.36	0.68
Age of Spouse | Married	34.18	7.02	34.76	7.23	37.07	7.14	37.59	7.58
Education of Spouse | Married	14.18	1.97	14.03	1.98	13.86	2.09	13.90	2.10
Log Wage of Spouse | Married	2.77	0.65	2.73	0.66	3.08	0.61	3.15	0.65
Log Hours of Spouse | Married	6.92	1.00	6.94	0.95	7.55	0.65	7.54	0.63
Spouse Employed | Married	0.77	0.42	0.75	0.43	0.91	0.28	0.90	0.30
Spouse Unemployed | Married	0.05	0.22	0.06	0.23	0.05	0.21	0.05	0.22
Spouse Nonparticipation | Married	0.18	0.39	0.19	0.39	0.04	0.20	0.05	0.21
Log earnings of Spouse | Married	9.63	1.48	9.68	1.44	10.64	1.11	10.70	1.08
Log Family Income	11.04	0.84	11.07	0.87	10.96	0.87	11.04	0.91
Level of Family Income	84168.74	68636.65	87919.86	69597.17	78907.39	65295.62	88042.95	72177.32
Log of Unearned Income	7.29	1.45	7.49	1.24	7.43	1.51	7.63	1.28
Level of Unearned Income	5639.31	15824.97	4759.88	11152.15	6532.97	17931.21	5571.57	12611.53
Log Family Income AE	10.42	0.80	.	.	10.30	0.84	.	.
Observations	14541		7270500		15737		7868500	

Table C.1c shows the means 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 1967–1980 cohort.

Table C.2a: Fit of Spouse Characteristics (Cohorts 35-44)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	1.030**	0.969	3.039**	0.129	0.062	-0.466**
	(0.471)	(0.694)	(1.366)	(1.753)	(0.176)	(0.197)
Education	0.533***	0.813***				
	(0.001)	(0.002)				
Log Wage					0.211***	0.241***
					(0.002)	(0.003)
Education × PSID Data	-0.079**	-0.084				
	(0.037)	(0.053)				
Log Wage × PSID					0.017	0.120
					(0.061)	(0.074)
Age spline 25-31			0.853***	1.014***		
			(0.002)	(0.003)		
Age spline 32-39			0.648***	0.999***		
			(0.006)	(0.007)		
Age spline 40-47			0.816***	0.957***		
			(0.008)	(0.010)		
Age spline 48-55			0.752***	1.009***		
			(0.010)	(0.013)		
Age spline 25-31 × PSID Data			-0.136**	0.038		
			(0.059)	(0.083)		
Age spline 32-39 × PSID Data			0.204	-0.302		
			(0.149)	(0.207)		
Age spline 40-47 × PSID Data			0.032	0.074		
			(0.225)	(0.328)		
Age spline 48-55 × PSID Data			0.309	-0.086		
			(0.230)	(0.372)		
Constant	5.737***	2.778***	1.556***	2.067***	1.818***	2.440***
	(0.019)	(0.025)	(0.055)	(0.063)	(0.007)	(0.008)
R-squared	0.42	0.50	0.77	0.82	0.06	0.05
Observations	3747266	3560993	794088	723864	286958	220498

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

Table C.2a displays, for the 1935–1944 cohorts, 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 characteristics, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.2b: Fit of Spouse Characteristics (Cohorts 45-62)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	-0.329	0.149	0.935	0.502	-0.109	-0.105
	(0.306)	(0.360)	(0.777)	(0.792)	(0.074)	(0.069)
Education	0.544***	0.694***				
	(0.001)	(0.001)				
Log Wage					0.224***	0.246***
					(0.001)	(0.001)
Education × PSID Data	0.028	-0.011				
	(0.023)	(0.026)				
Log Wage × PSID					0.070***	0.001
					(0.025)	(0.025)
Age spline 25-31			0.895***	0.959***		
			(0.002)	(0.002)		
Age spline 32-39			0.830***	0.881***		
			(0.003)	(0.003)		
Age spline 40-47			0.862***	0.911***		
			(0.004)	(0.005)		
Age spline 48-55			0.860***	0.928***		
			(0.006)	(0.008)		
Age spline 25-31 × PSID Data			-0.041	-0.024		
			(0.032)	(0.034)		
Age spline 32-39 × PSID Data			0.125*	0.080		
			(0.067)	(0.075)		
Age spline 40-47 × PSID Data			-0.102	-0.154		
			(0.096)	(0.099)		
Age spline 48-55 × PSID Data			-0.100	0.264*		
			(0.131)	(0.150)		
Constant	6.038***	4.282***	1.447***	3.611***	1.891***	2.377***
	(0.014)	(0.016)	(0.038)	(0.039)	(0.003)	(0.003)
R-squared	0.34	0.40	0.75	0.74	0.05	0.06
Observations	10991116	10912900	2527737	2479062	1365214	1140934

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

Table C.2b displays, for the 1945–1962 cohorts, 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 characteristics, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.2c: Fit of Spouse Characteristics (Cohorts 67-80)

	Spouse's Education		Spouse's Age		Spouse's Wage	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
PSID Data	-0.043	-0.799*	0.659	2.225**	-0.328***	-0.331***
	(0.384)	(0.447)	(1.378)	(1.125)	(0.090)	(0.086)
Education	0.589***	0.594***				
	(0.001)	(0.001)				
Log Wage					0.225***	0.224***
					(0.001)	(0.001)
Education × PSID Data	0.014	0.054*				
	(0.027)	(0.031)				
Log Wage × PSID					0.115***	0.076**
					(0.031)	(0.030)
Age spline 25-31			0.854***	0.923***		
			(0.002)	(0.002)		
Age spline 32-39			0.778***	0.871***		
			(0.004)	(0.004)		
Age spline 40-47			0.903***	0.865***		
			(0.008)	(0.008)		
Age spline 48-55			0.939***	0.890***		
			(0.029)	(0.032)		
Age spline 25-31 × PSID Data			-0.033	-0.087*		
			(0.052)	(0.045)		
Age spline 32-39 × PSID Data			0.004	0.056		
			(0.076)	(0.089)		
Age spline 40-47 × PSID Data			-0.321*	-0.024		
			(0.168)	(0.196)		
Age spline 48-55 × PSID Data			1.846***	0.607		
			(0.619)	(0.538)		
Constant	5.911***	5.475***	3.278***	4.696***	2.021***	2.412***
	(0.018)	(0.021)	(0.055)	(0.056)	(0.004)	(0.004)
R-squared	0.36	0.30	0.59	0.57	0.05	0.05
Observations	5103820	5546005	1548450	1673817	931884	951004

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

Table C.2c displays, for the 1935–1944 cohorts, 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 characteristics, as well as interactions with whether the data comes from the PSID or is simulated.

Table C.3a: Dynamic Fit (Cohorts 35-44)

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	0.591	0.476	0.497	0.830	0.737	0.683	0.615	0.836	0.707
	(0.007)		(0.008)		(0.009)		(0.007)		(0.008)		(0.007)	
3	0.718	0.714	0.619	0.391	0.317	0.199	0.753	0.620	0.580	0.268	0.759	0.575
	(0.008)		(0.010)		(0.010)		(0.009)		(0.009)		(0.008)	
6	0.669	0.652	0.544	0.270	0.282	0.115	0.735	0.549	0.500	0.103	0.721	0.488
	(0.010)		(0.014)		(0.012)		(0.014)		(0.012)		(0.010)	
8	0.638	0.628	0.554	0.232	0.263	0.100	0.748	0.528	0.453	0.068	0.690	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	0.767	0.833	0.728	0.476	0.667	0.896	0.777	0.704	0.632	0.839	0.720
	(0.008)		(0.006)		(0.009)		(0.004)		(0.008)		(0.006)	
3	0.657	0.684	0.685	0.555	0.317	0.453	0.769	0.621	0.570	0.284	0.768	0.568
	(0.008)		(0.008)		(0.010)		(0.007)		(0.009)		(0.008)	
6	0.623	0.616	0.550	0.432	0.282	0.358	0.652	0.507	0.462	0.111	0.721	0.465
	(0.010)		(0.009)		(0.012)		(0.008)		(0.012)		(0.010)	
8	0.595	0.592	0.486	0.382	0.263	0.326	0.589	0.460	0.388	0.071	0.707	0.425
	(0.012)		(0.010)		(0.013)		(0.010)		(0.013)		(0.012)	

Table C.3a shows the dynamic fit of the model for the 1935–1944 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 (Cohorts 45-62)

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	0.629	0.509	0.514	0.825	0.744	0.605	0.589	0.822	0.716
	(0.004)		(0.004)		(0.006)		(0.004)		(0.007)		(0.004)	
3	0.669	0.694	0.565	0.437	0.342	0.232	0.708	0.607	0.479	0.236	0.734	0.570
	(0.004)		(0.007)		(0.007)		(0.006)		(0.008)		(0.006)	
6	0.625	0.621	0.469	0.317	0.264	0.143	0.643	0.518	0.405	0.086	0.686	0.469
	(0.006)		(0.008)		(0.007)		(0.008)		(0.008)		(0.007)	
8	0.600	0.592	0.437	0.280	0.231	0.120	0.615	0.488	0.361	0.054	0.672	0.430
	(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	0.683	0.509	0.620	0.874	0.75	0.634	0.610	0.777	0.726
	(0.004)		(0.004)		(0.006)		(0.003)		(0.006)		(0.004)	
3	0.644	0.680	0.628	0.497	0.342	0.397	0.726	0.586	0.497	0.259	0.689	0.566
	(0.004)		(0.004)		(0.007)		(0.004)		(0.008)		(0.006)	
6	0.606	0.616	0.474	0.382	0.264	0.310	0.591	0.479	0.384	0.098	0.653	0.453
	(0.006)		(0.006)		(0.007)		(0.006)		(0.008)		(0.007)	
8	0.574	0.595	0.395	0.342	0.231	0.287	0.515	0.444	0.326	0.061	0.625	0.409
	(0.006)		(0.007)		(0.007)		(0.007)		(0.008)		(0.008)	

Table C.3b shows the dynamic fit of the model for the 1945–1962 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 (Cohorts 67-80)

Panel A: Men

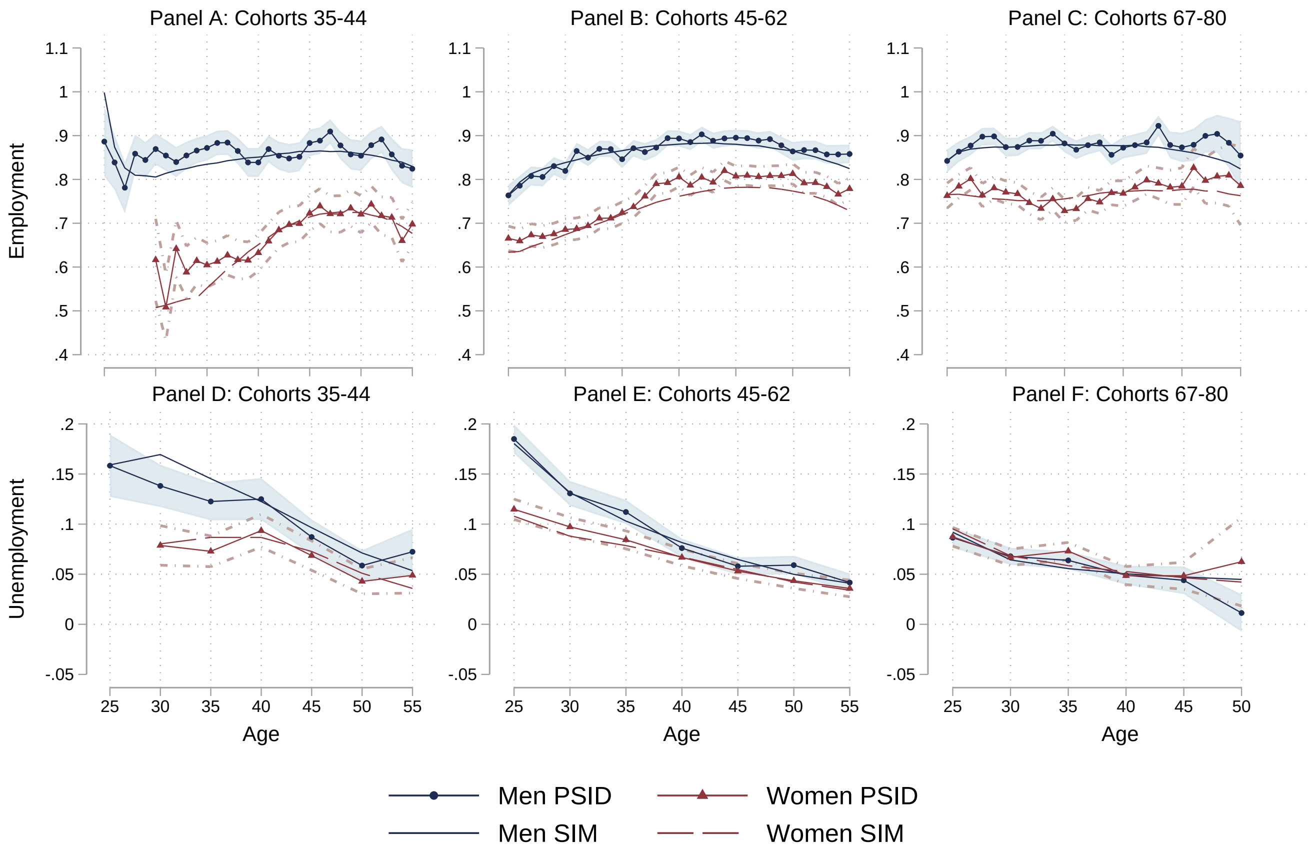
	Wages		*Hours*		*Employment*		*Earnings*		*Unearned Income*		*Family Income*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Lag	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM	PSID	SIM
1	0.713	0.753	0.773	0.675	0.519	0.566	0.879	0.760	0.388	0.547	0.711	0.737
	(0.006)		(0.006)		(0.008)		(0.004)		(0.043)		(0.019)	
3	0.656	0.675	0.595	0.488	0.349	0.331	0.765	0.620	0.226	0.202	0.591	0.587
	(0.007)		(0.008)		(0.009)		(0.008)		(0.059)		(0.028)	
6	0.634	0.606	0.531	0.375	0.264	0.246	0.712	0.529	0.312	0.074	0.681	0.485
	(0.008)		(0.010)		(0.010)		(0.010)		(0.016)		(0.013)	
8	0.606	0.579	0.469	0.340	0.217	0.217	0.679	0.500	0.268	0.046	0.633	0.444
	(0.010)		(0.013)		(0.012)		(0.013)		(0.017)		(0.014)	

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	0.708	0.749	0.800	0.667	0.519	0.603	0.884	0.740	0.300	0.578	0.582	0.726
	(0.006)		(0.006)		(0.008)		(0.004)		(0.050)		(0.021)	
3	0.646	0.665	0.625	0.479	0.349	0.386	0.749	0.577	0.226	0.225	0.446	0.558
	(0.007)		(0.008)		(0.009)		(0.007)		(0.067)		(0.029)	
6	0.586	0.598	0.483	0.367	0.264	0.305	0.637	0.476	0.377	0.090	0.657	0.439
	(0.008)		(0.009)		(0.010)		(0.009)		(0.014)		(0.012)	
8	0.560	0.578	0.430	0.328	0.217	0.280	0.587	0.444	0.314	0.056	0.623	0.395
	(0.009)		(0.012)		(0.012)		(0.012)		(0.017)		(0.014)	

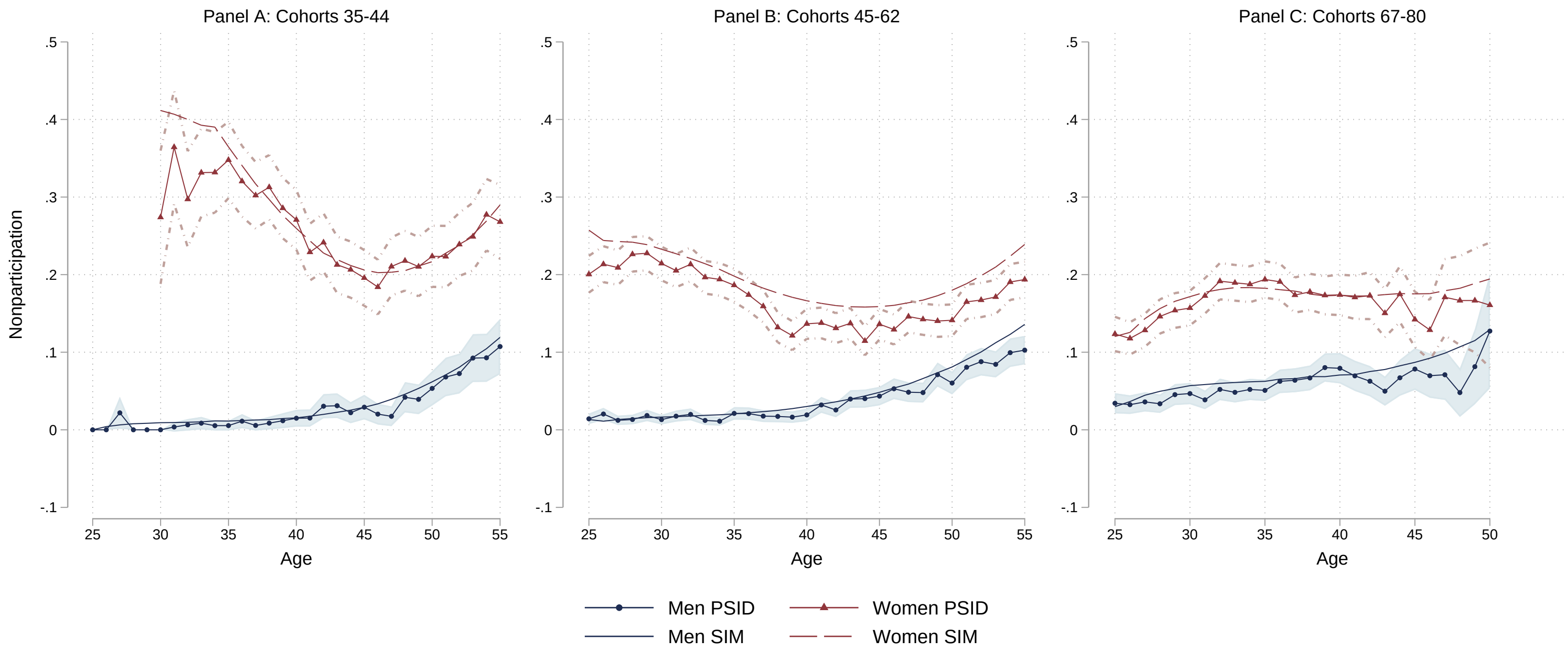
Table C.3c shows the dynamic fit of the model for the 1967–1980 cohort. Each row in the table shows the coefficient, or standard error, estimated when regressing each outcome variable on its own k-*th* lag, as indicated in the leftmost column, using the PSID and simulated data, respectively. Simulations 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



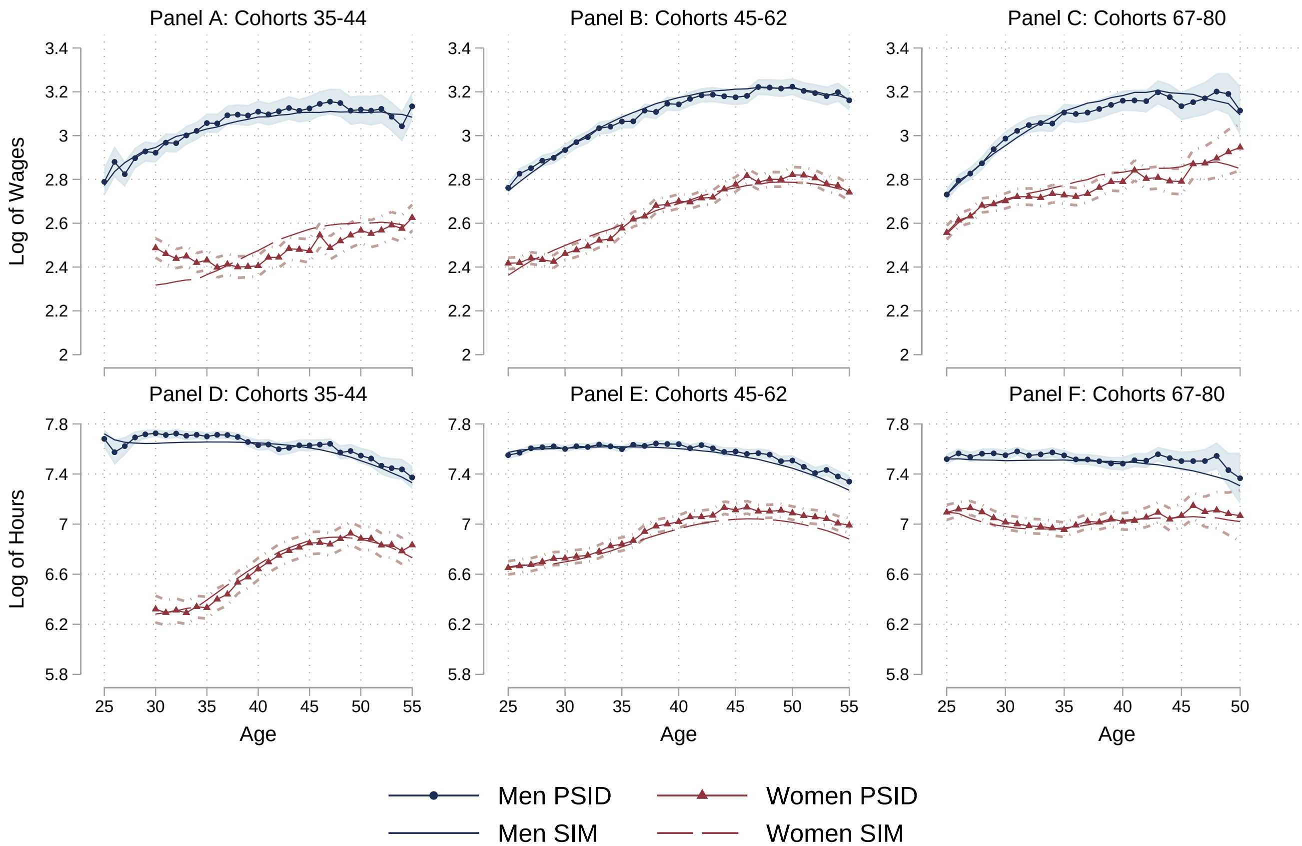
Figures C.1-C.10 display the average values of each key variable at each age for data simulated using the model with estimated parameters and 500 copies per PSID sample member, and the PSID data. The data is graphed separately by cohort group. Because wives' unemployment information is not available in the first five years of the survey, we omit the first ages for women from the 1935–1944 cohort in this and all subsequent fit figures. 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 indicate the same for PSID female sample members. In figure D1, 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



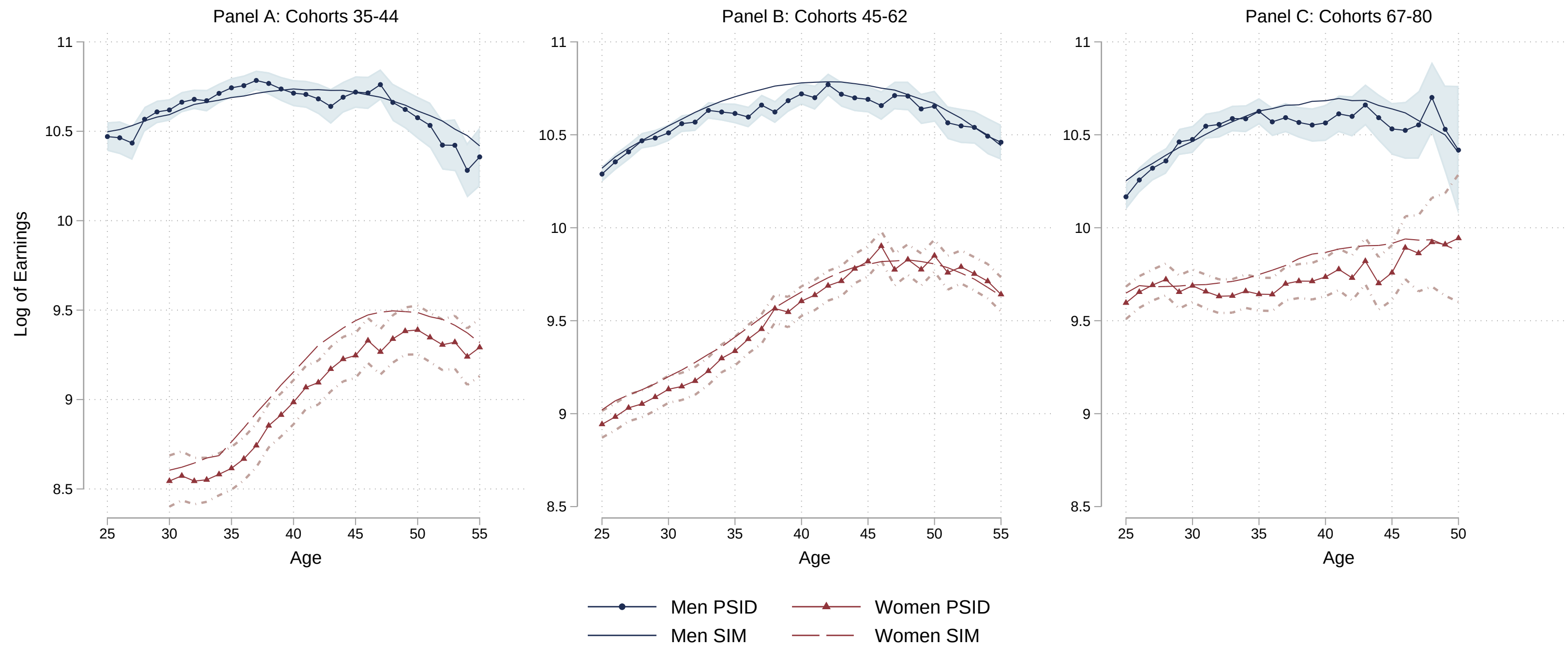
See Figure C.1 notes for further description.

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



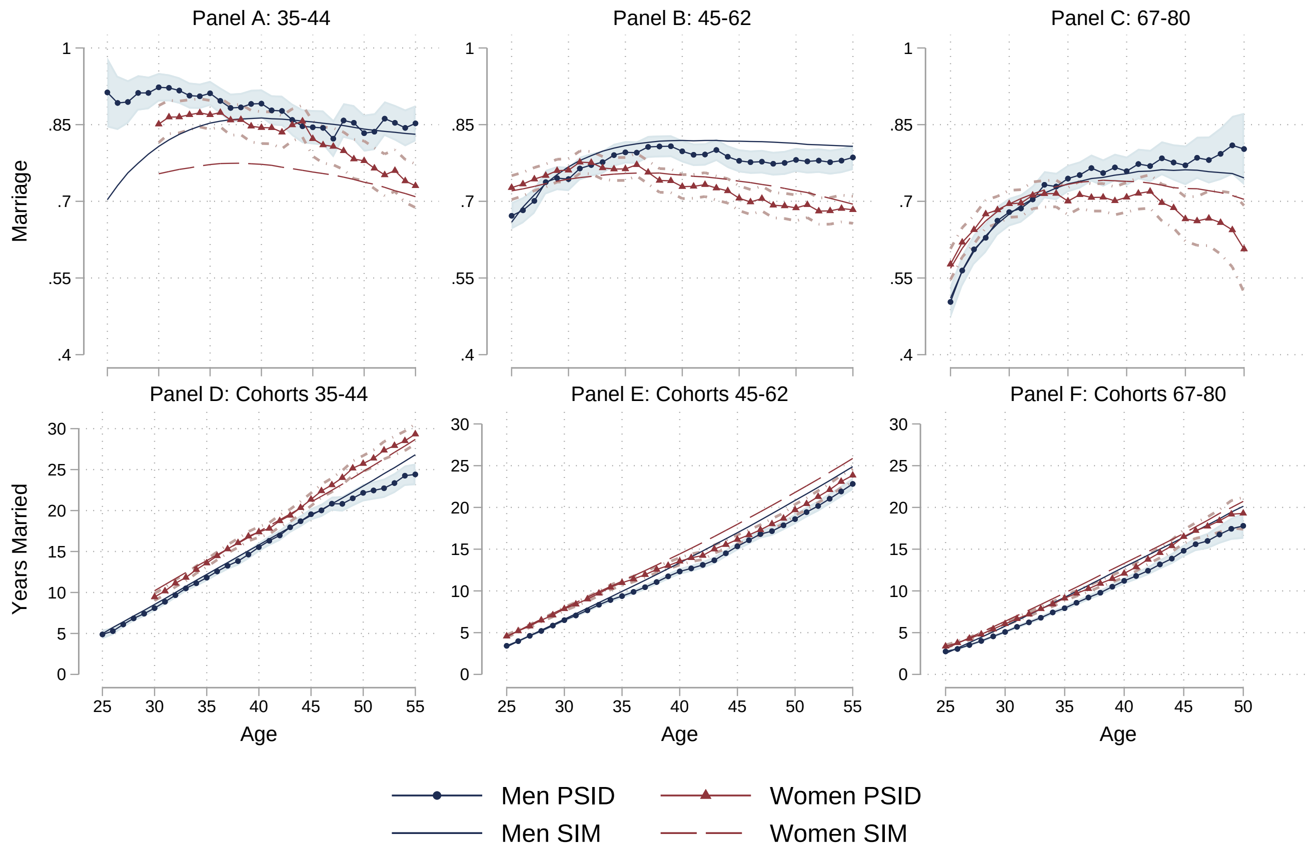
See Figure C.1 notes for further description.

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



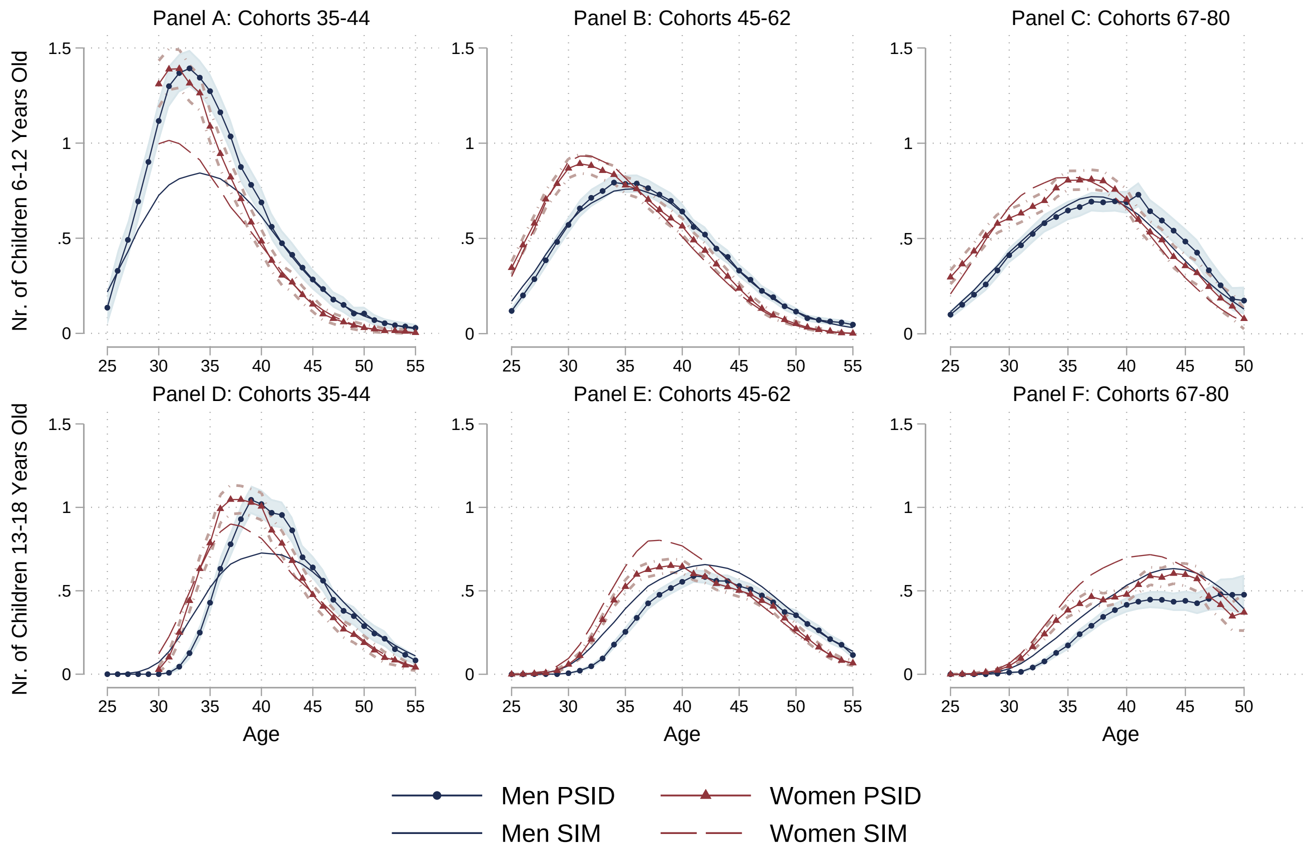
See Figure C.1 notes for further description.

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



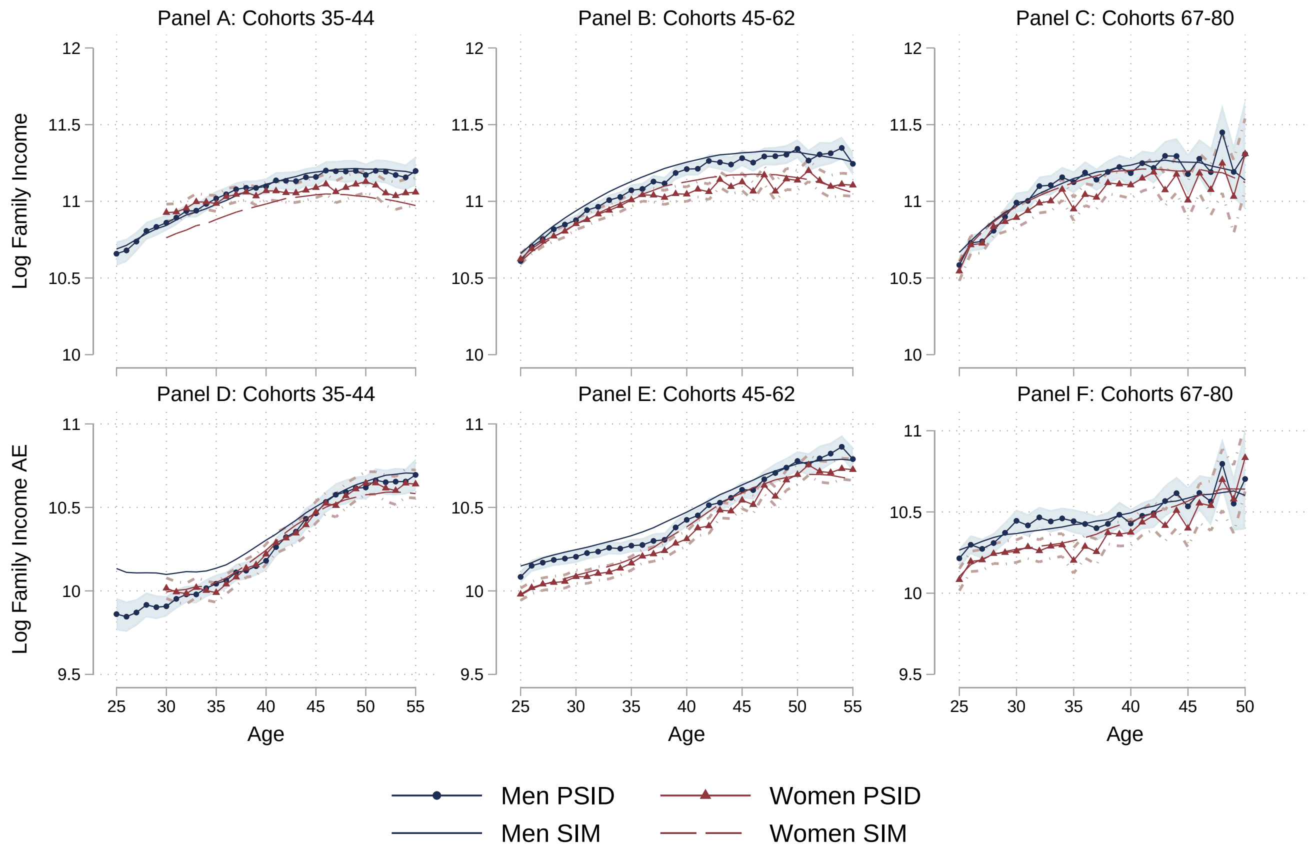
See Figure C.1 notes for further description.

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



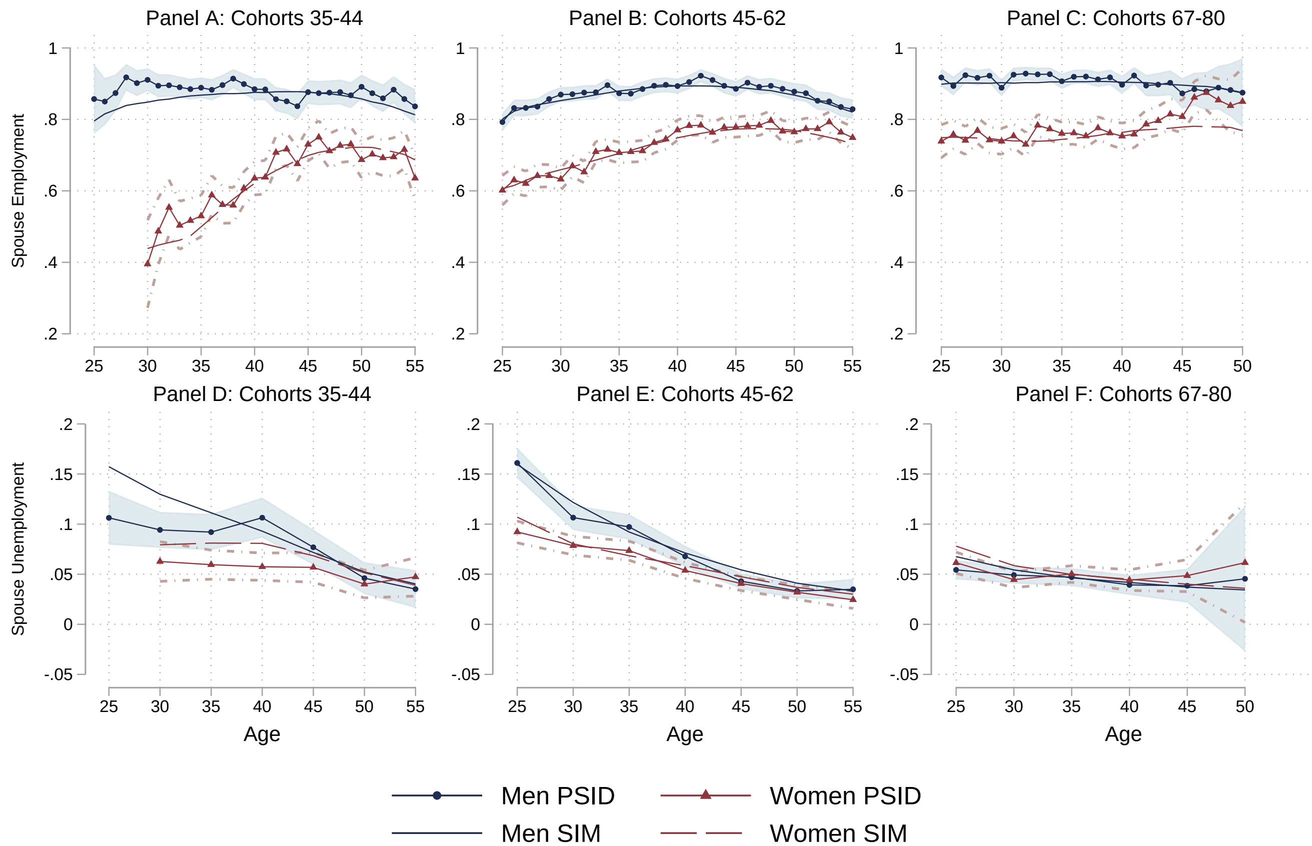
See Figure C.1 notes for further description.

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



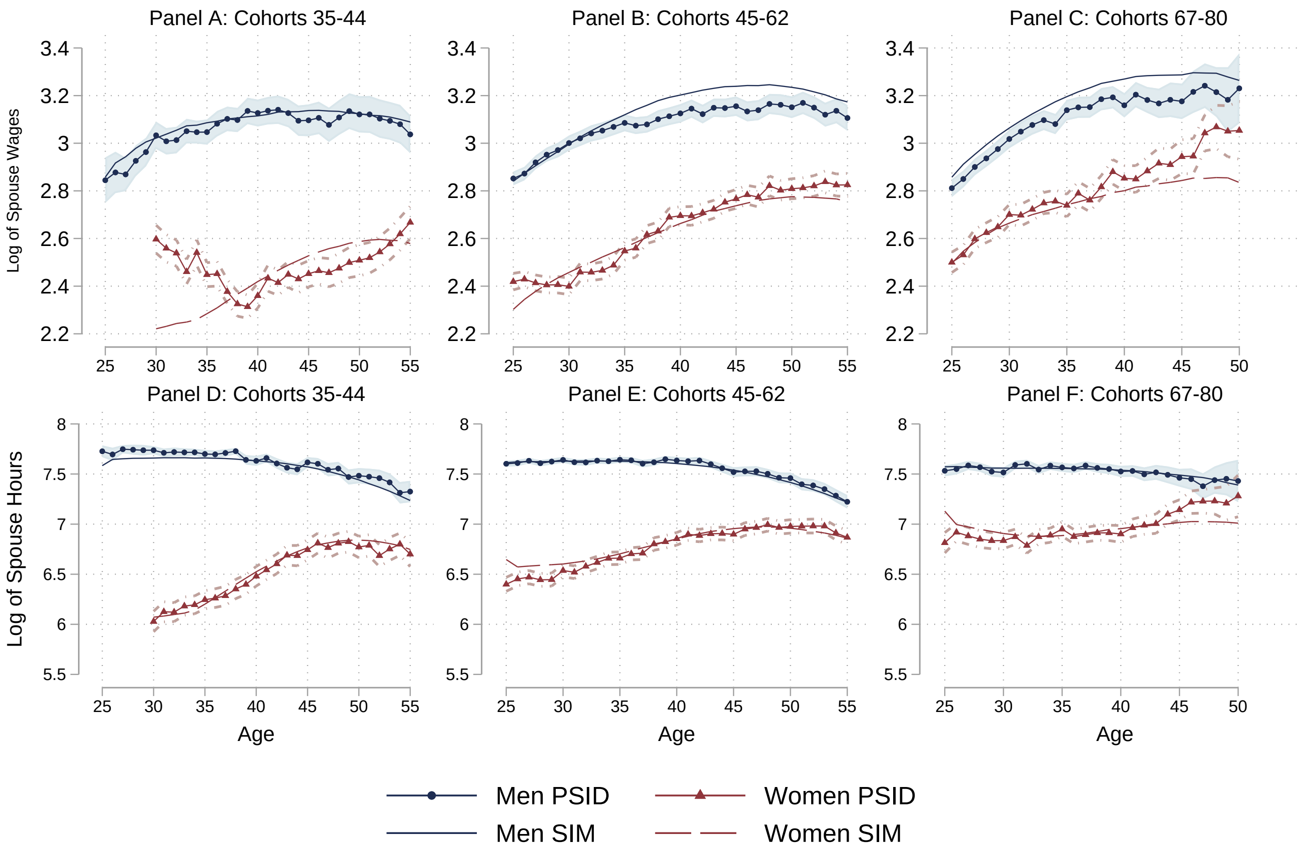
See Figure C.1 notes for further description.

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



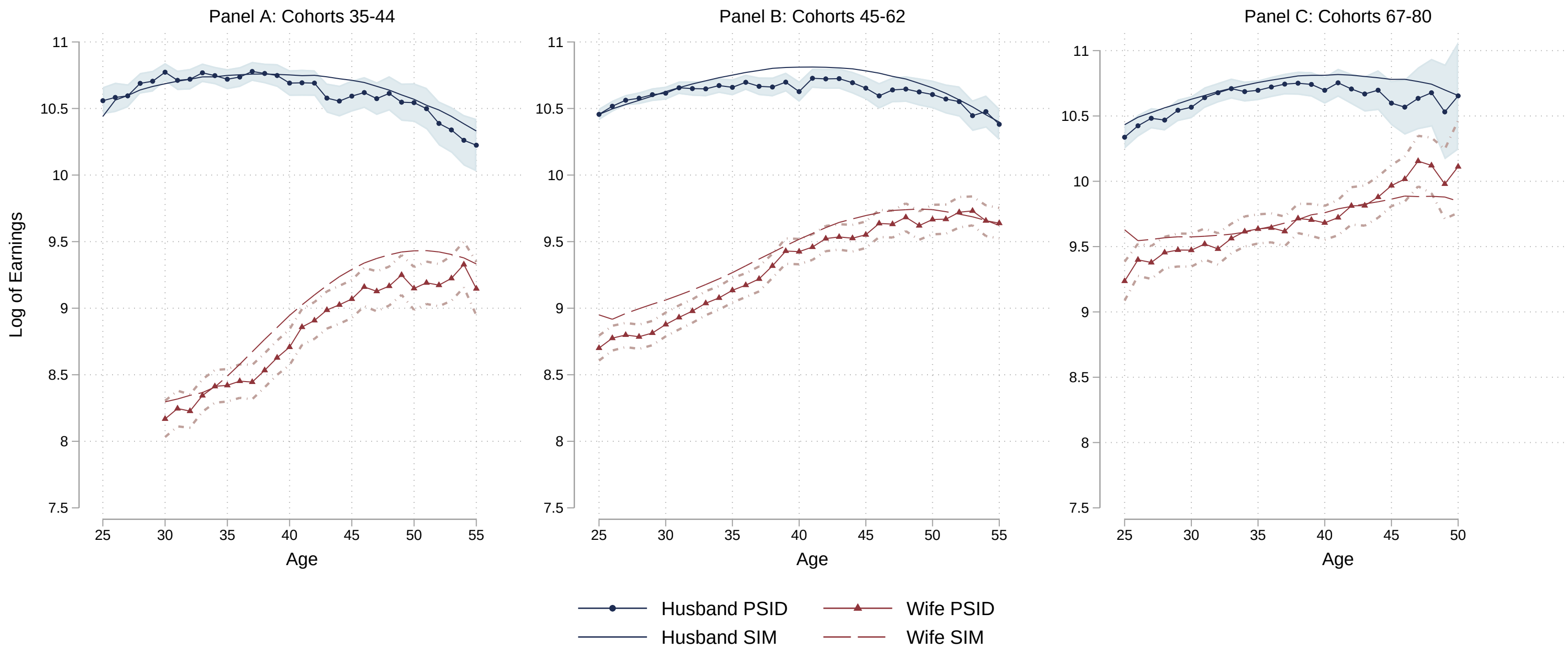
See Figure C.1 notes for further description.

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



See Figure C.1 notes for further description.

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



See Figure C.1 notes for further description.

Appendix D Additional Impulse Response Estimates

Figure D.1: Response of Employment Probability to a Divorce Shock

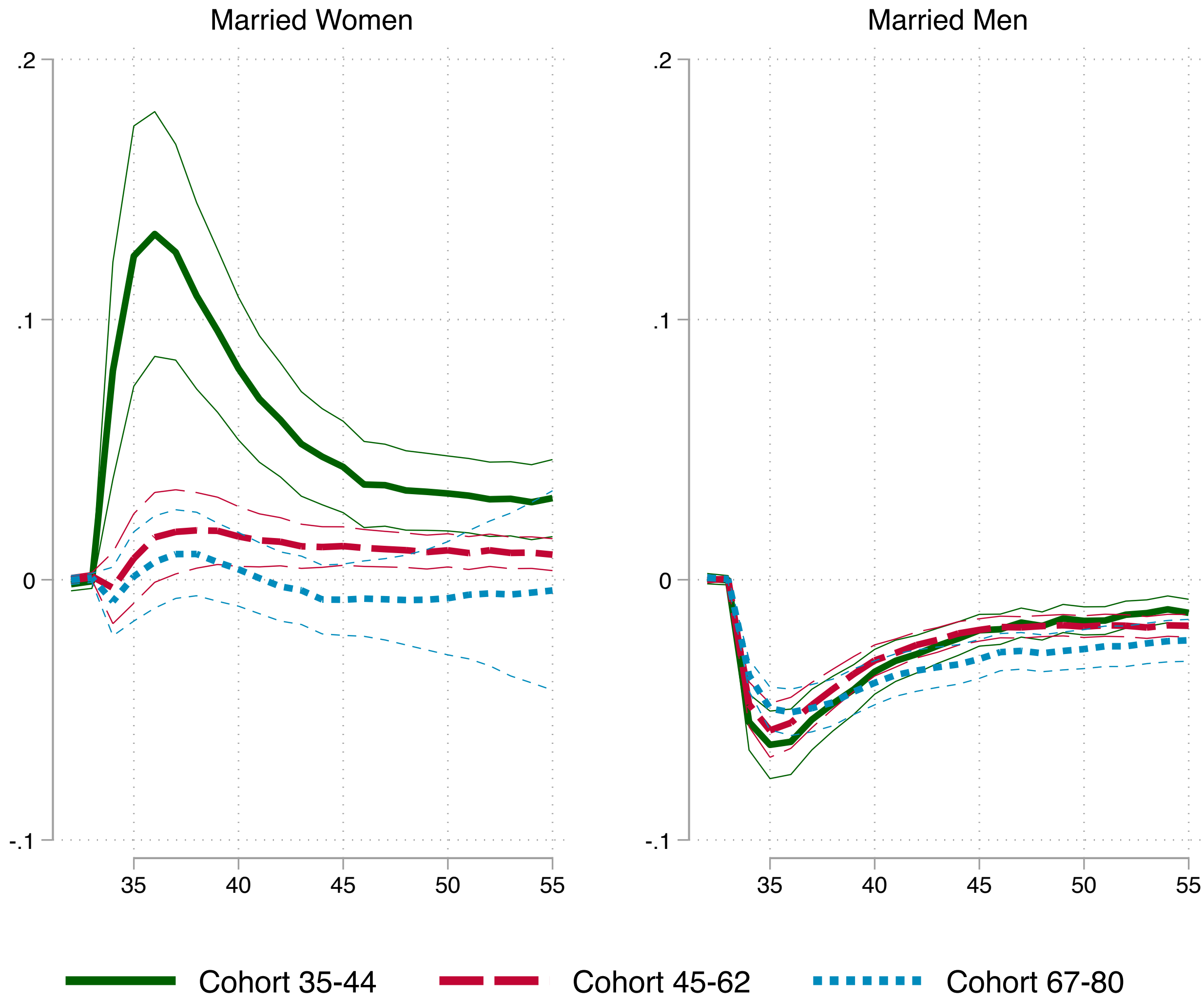


Figure D.1 displays the effect of exogenously imposing a divorce shock on employment. The analysis is peformed separately by cohort and gender. The long solid line shows the effect for the 1935–1944 cohort, the long dashes for the 1945–1962 cohort, and the short dshes for the 1967–1980 cohort. The corresponding thinner lines trace 90% confidence bands. To obtain the results, we use the same method as explained in the note to figure 1.

Figure D.2a: Response of Hours, Wage, and Earnings to a Marriage Shock

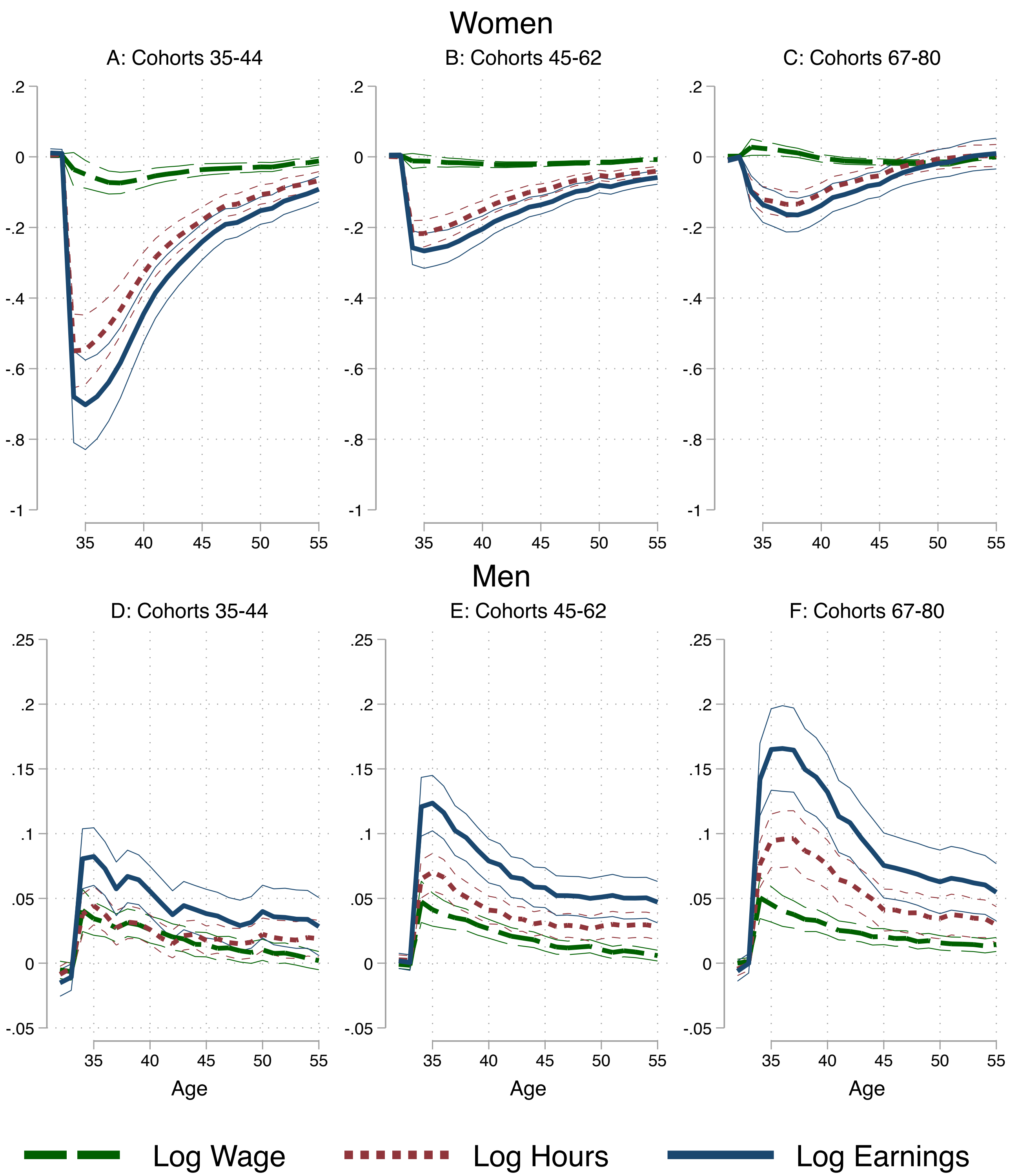


Figure D.2a displays the effect of exogenously imposing a marriage shock on wages, hours, and earnings. To obtain the results, we use the same method as explained in the note to figure 1, except imposing that all single people get married at age 34.

Figure D.2b: Response of Family Earnings and Family Income Per Adult Equivalent to a Marriage Shock

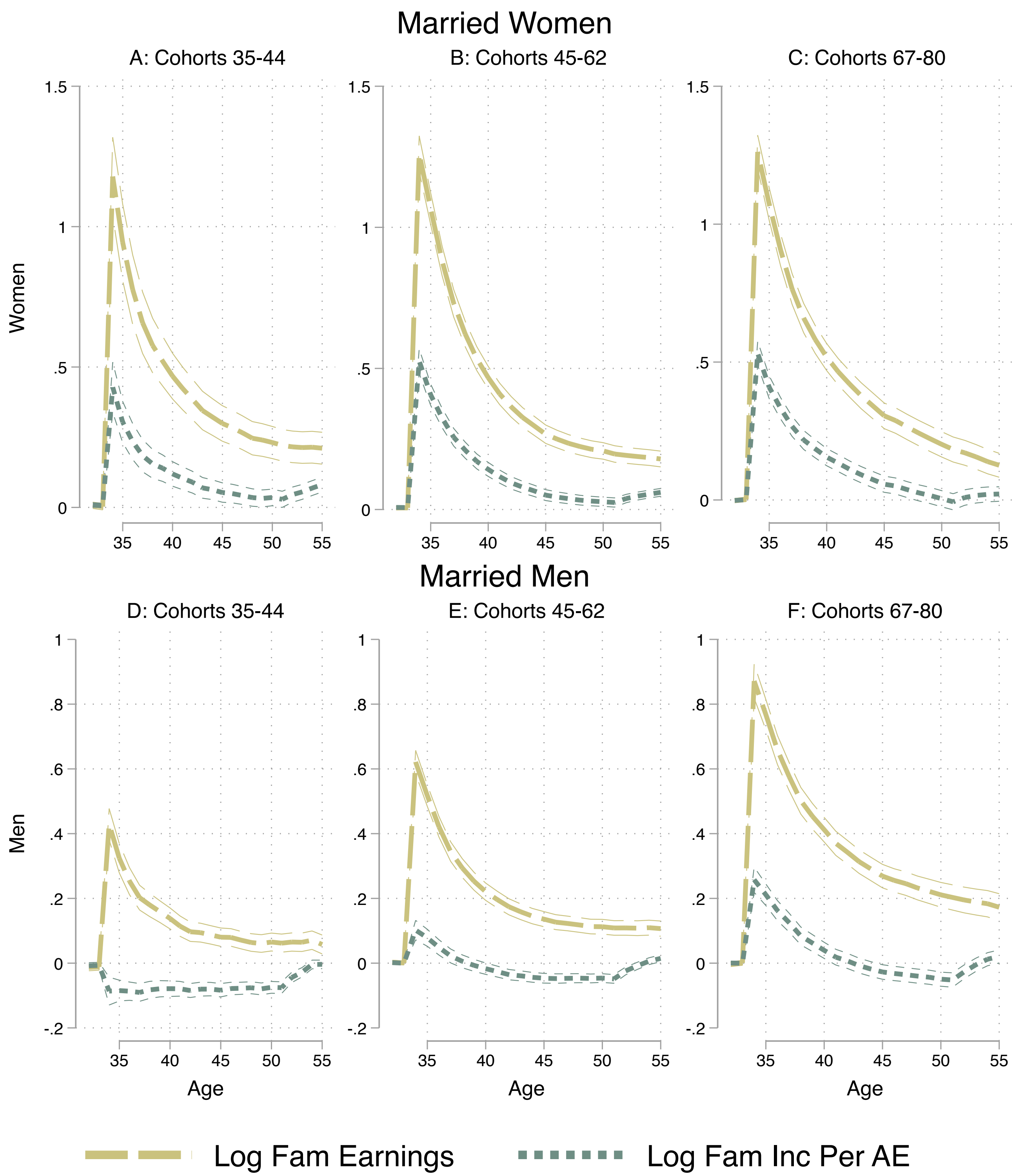


Figure D.2b displays the effect of exogenously imposing a marriage shock on household income and earnings variables. To obtain the results, we use the same method as explained in the note to figure 1, except imposing that all single people get married at age 34.

Figure D.3: Response of Earnings, Family Earnings, and Family Income Per Adult Equivalent to an Unemployment Shock for Single Women and Men

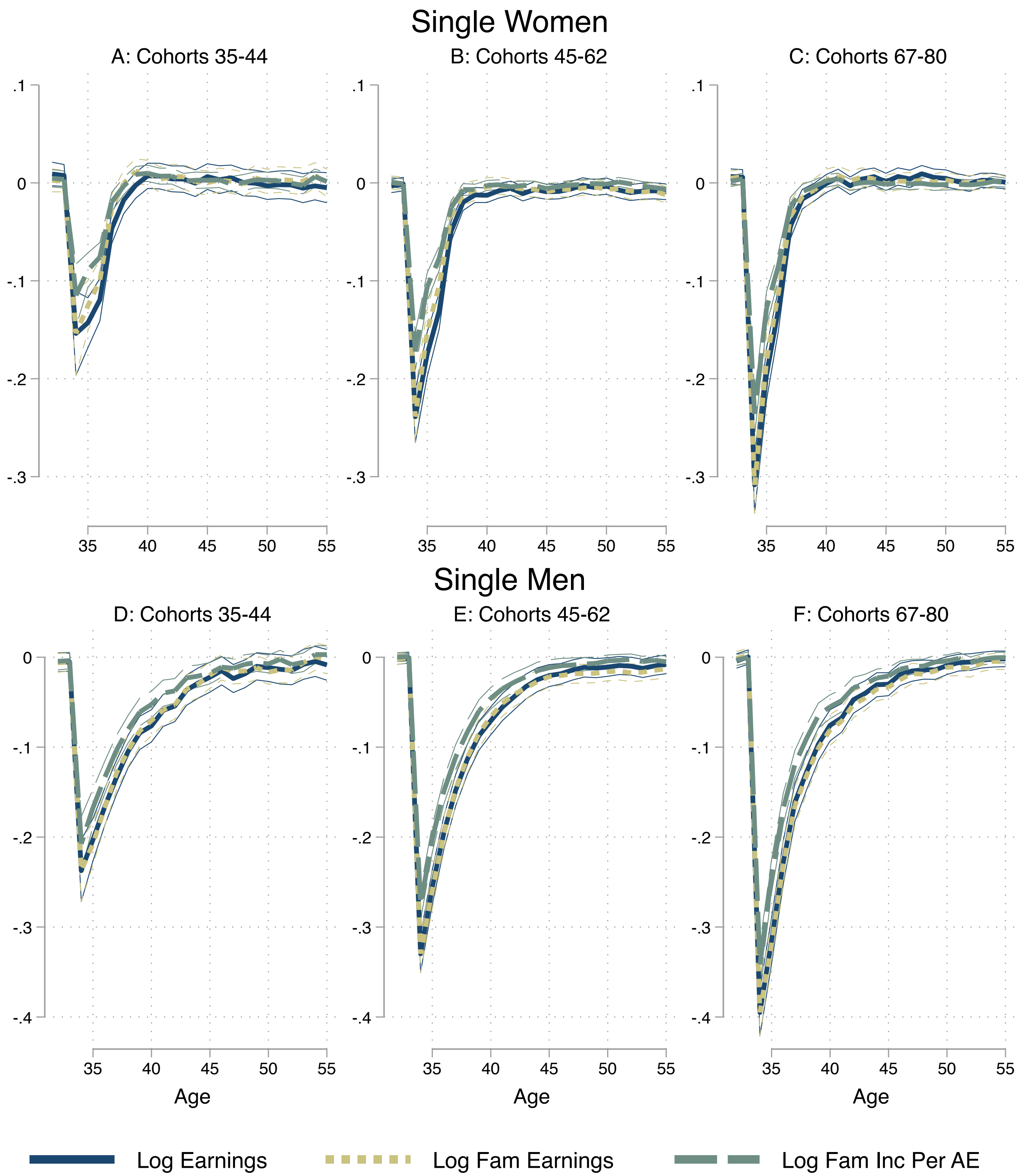


Figure D.3 displays the effect of an exogenously imposed unemployment shock on single women and men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead that all individuals in the labor force are unemployed at age 34.

Figure D.4: Response of Earnings, Family Earnings and Family Income Per Adult Equivalent to a Wage Shock for Single Women and Men

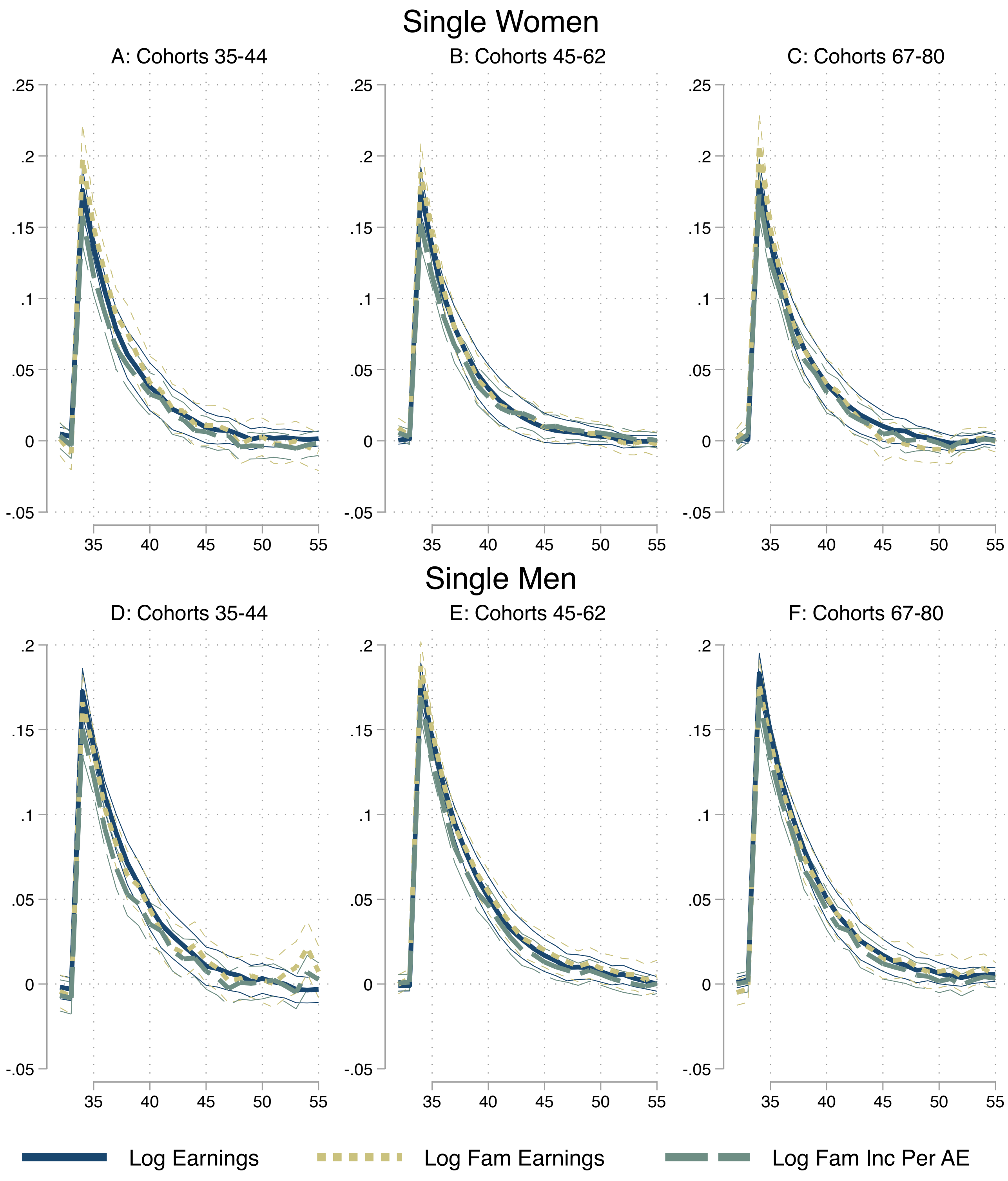


Figure D.4 displays the effect of an exogenously imposed wage shock on single women and men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead a 1 SD increase in the autoregressive component of wages on all individuals at age 34.

Figure D.5: Response of Marriage Probability to a Childbirth Shock

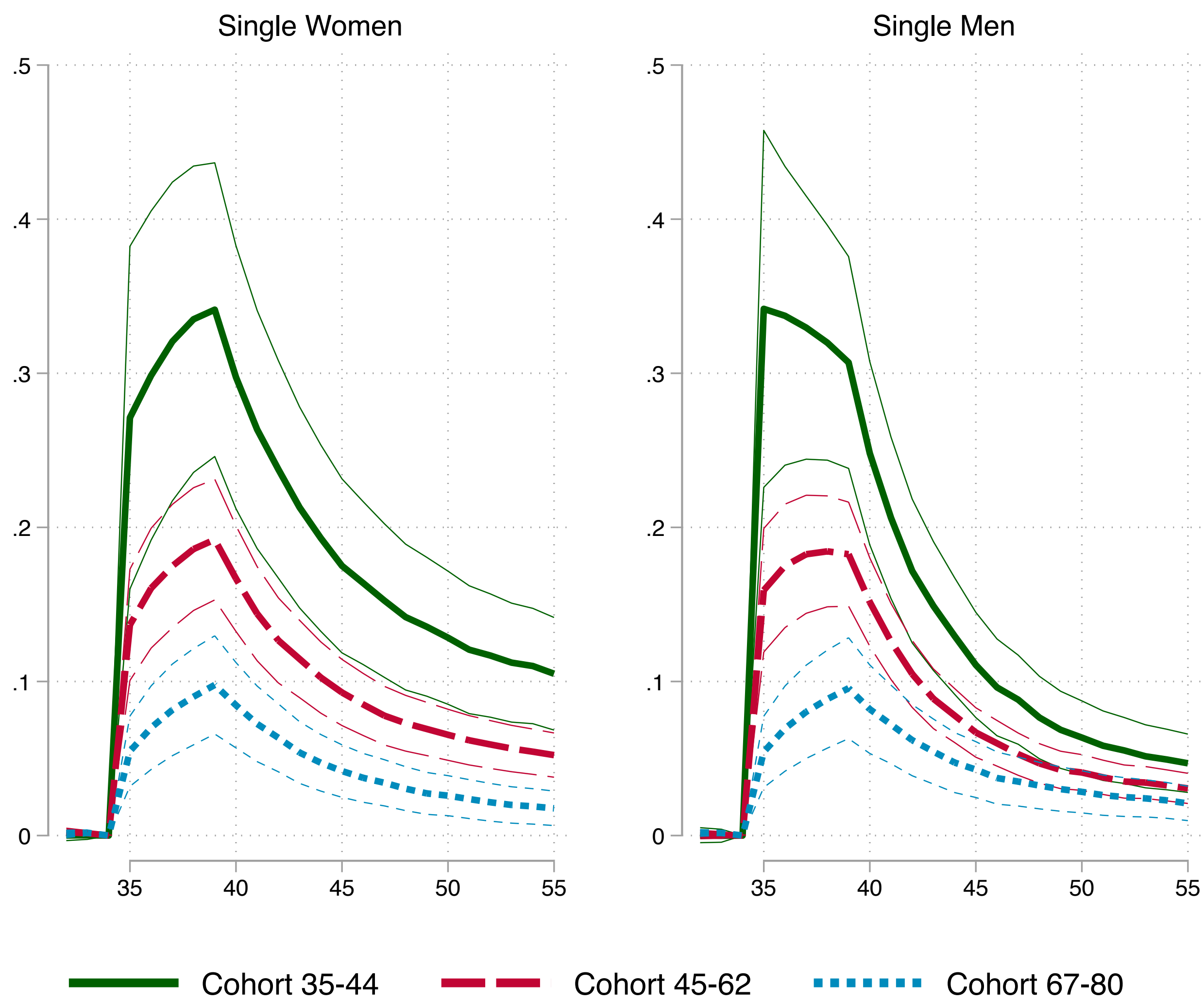


Figure D.5 displays the effect of an exogenously imposed childbirth shock on single women and men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead that all individuals have a child at age 34.

Figure D.6: Response to a Childbirth Shock of Earnings, Family Earnings, and Family Income per Adult Equivalent for Men

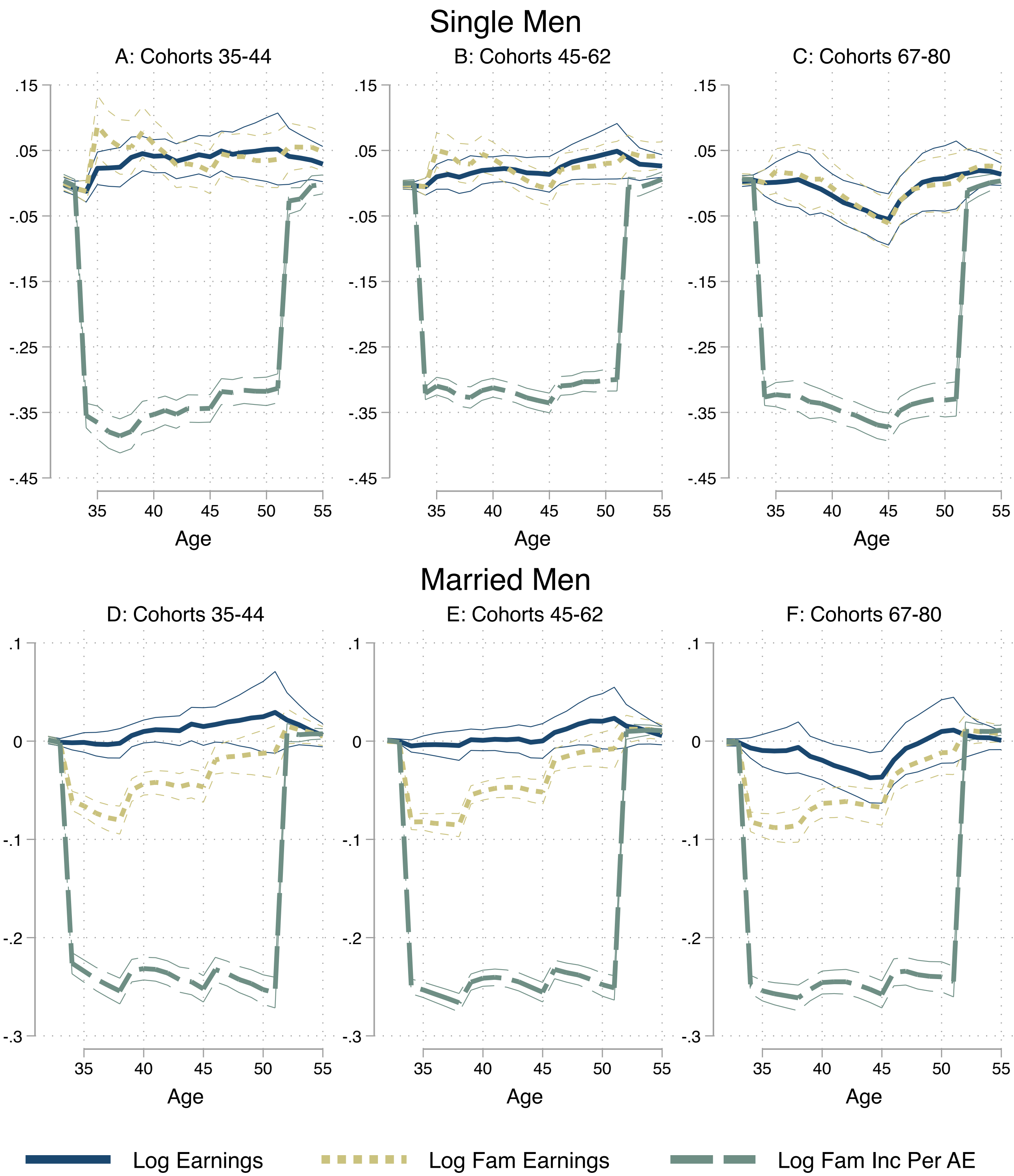


Figure D.6 displays the effect of an exogenously imposed childbirth shock on single and married men. To obtain the estimates, we use the same method as explained in the note to figure 1, but imposing instead that all individuals have a child at age 34.

Figure D.7: The Role of Marriage and Sorting in the Response of Family Income Per Adult Equivalent to a Childbirth Shock

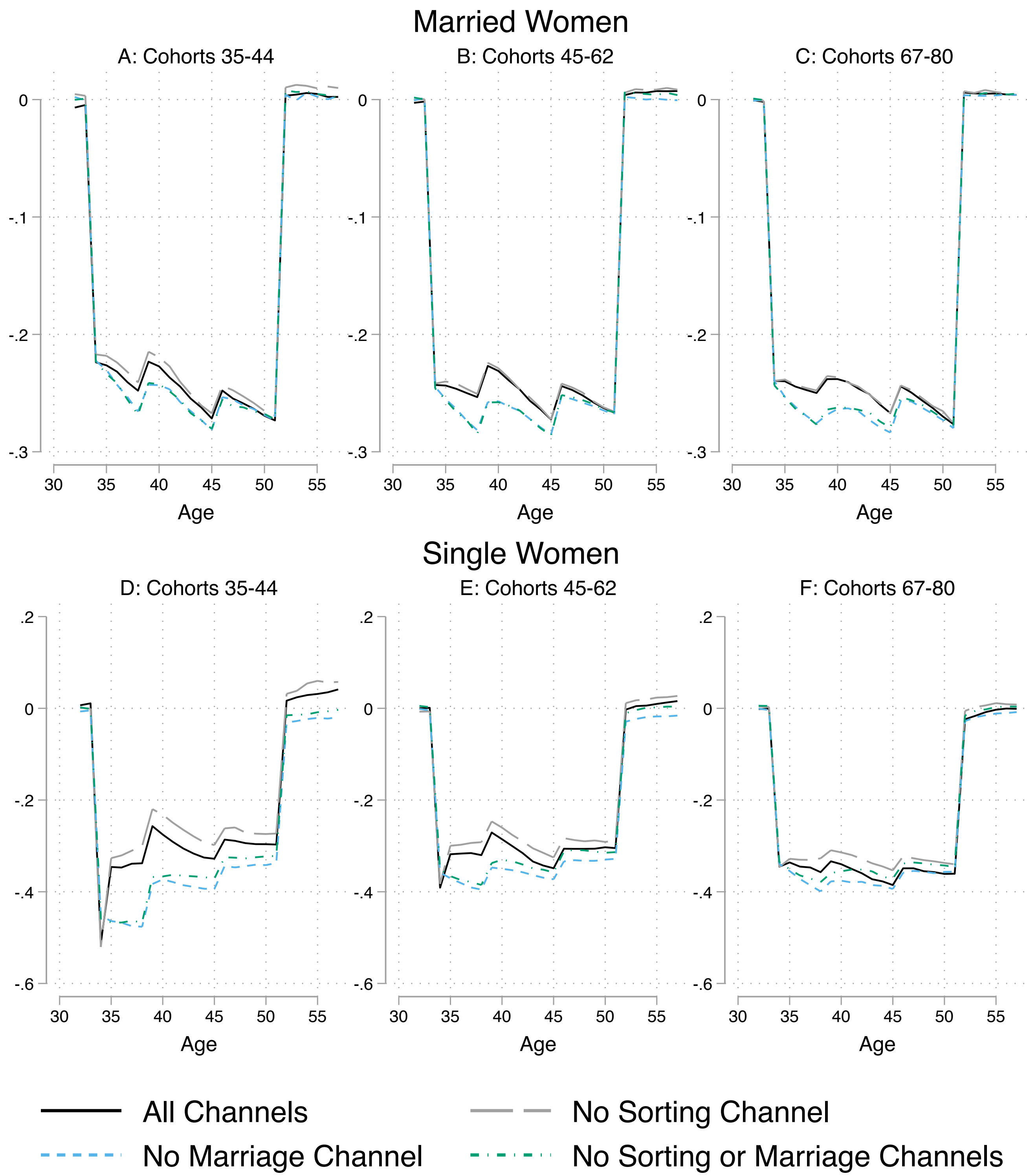


Figure D.7 displays the role of marriage and sorting in explaining the effect of a childbirth shock on family income per adult equivalent. To obtain these estimates, we use the method as explained in the note to figure 3, but instead considering the role of turning off each channel in the effect of the childbirth shock on log family income per adult equivalent.

Figure D.8: College - High School Gap in Wage, Hours, and Employment

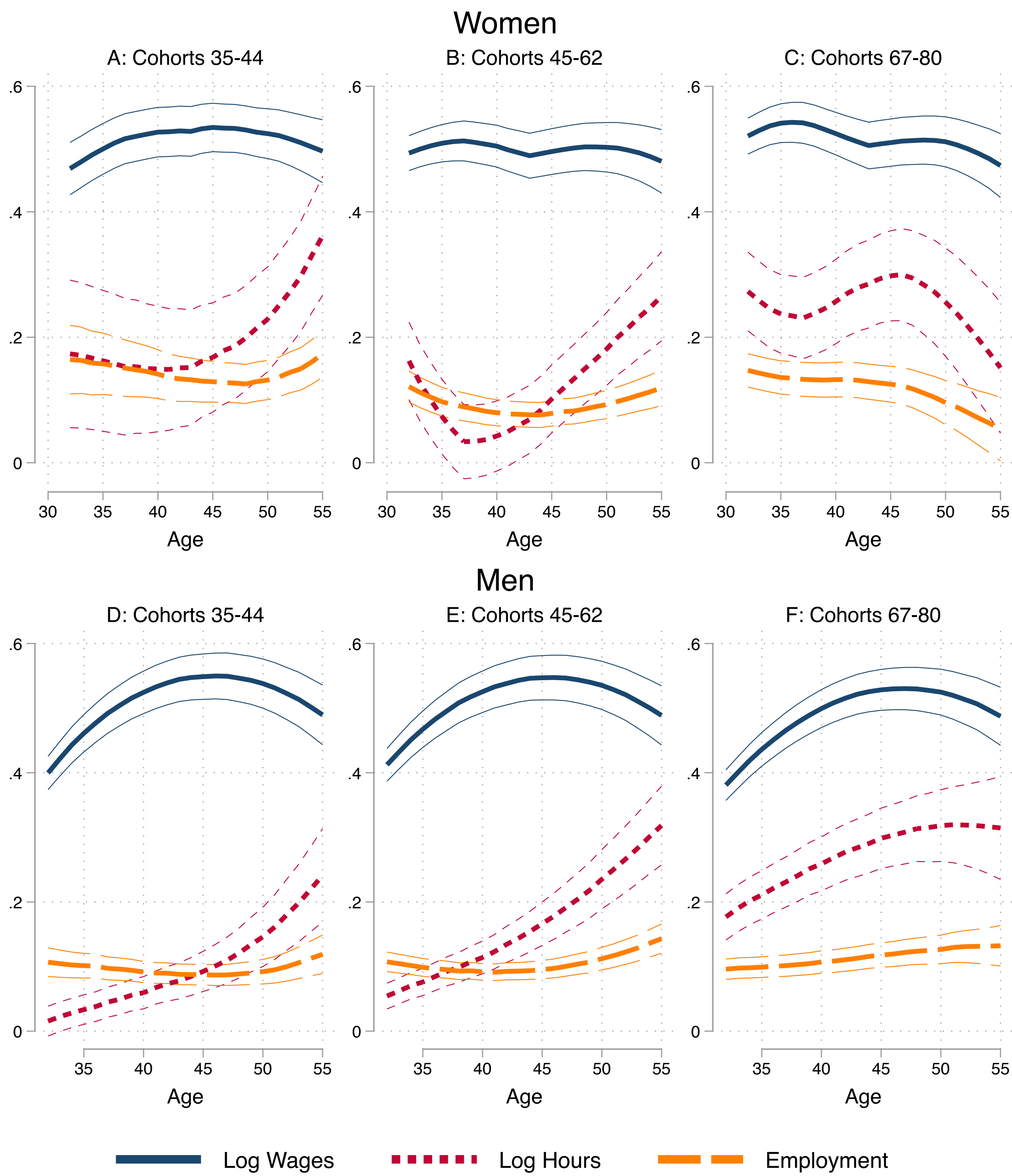


Figure D.8 displays the high-school versus college gap at each for men and women. To obtain the estimates, we followed the method explained in the note to figure 7.

Figure D.9: The Role of Marriage and Sorting in the Effect of a Permanent Wage on Family Income Per Adult Equivalent

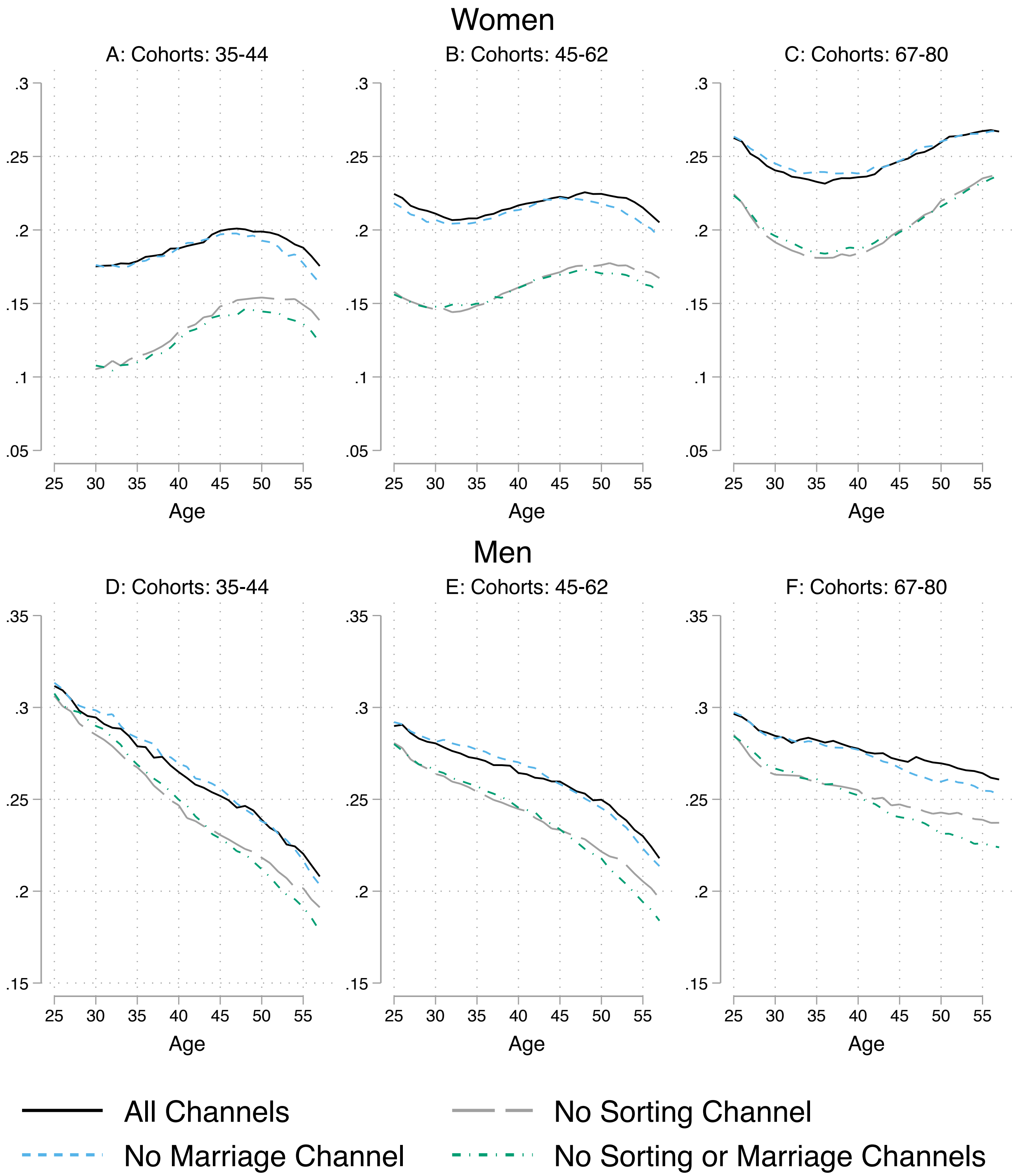


Figure D.9 displays the role of marriage and sorting in explaining the effect a 1 SD difference in the permanent wage component for men and women. To obtain the estimates, we use the same method as in figure 3, but imposing that all individuals begin with a 1 SD higher permanent wage component.

Appendix E Additional Variance Decomposition Tables

Appendix Tables E.1-E.3 present variance decompositions of the lifetime averages of a number of additional outcome variables—in addition to y_ae. The additional outcome variables are the lifetime average of: log earnings, log hourly wages, log work hours, log family earnings, log family unearned income, log family income, log family earnings per adult equivalent, and log family unearned income per adult equivalent. (The last row of the tables show the decompositions for y_ae, which are also shown in Figures 10 and 11.)

Tables E.1a, E.2a, and E.3a present the variance decompositions for women (for cohort groups 35–44, 45–62, and 67–80, respectively), while tables E.1b, E.2b, and E.3b present the corresponding decompositions for men. In each table, columns 1 to 12 show the percentage of the lifetime variance of a particular outcome that is explained by each factor. The row labels specify the outcome that is being decomposed. Bootstrap standard errors of the variance contributions are shown in parentheses.

Note that the contributions to the variances in columns 1-12 do not sum to 100%. This is for three reasons. (See also the discussion in Section 6.1 of AGHV.) First, because the model is nonlinear, interactions among the factors can amplify the contribution of some factors and can make the marginal contribution of some sources negative. Second, we do not separately measure the contributions of the spouse's post-marriage labor market shocks u^{ω}_{sit}, u^{h}_{sit}, ε^{h}_{sit}, ε^{w}_{sit}, the marriage match quality term $\xi_{j(i,t)}$, or the i.i.d. spousal employment shocks. Third, we do not consider the effect of random variation in the number of children. Column 16 of Tables E.1-E.3 shows the sum of percentages explained by the factors in columns 1-12. The difference between this value and 100 captures the combined contributions of the factors that we omit and the nonlinear interactions.

Columns 14 and 15 report the mean and standard deviation across individuals of the lifetime sum of each row variable, expressed on an annual basis. For example, in the case of log earnings (row 1), these columns report the mean and standard deviation (across i) of $earn_i$, where $earn_i = \Sigma_{t=25}^{55} earn_{it}/31$. (The magnitudes of the annualized lifetime sums are conceptually easier to think about, but this choice has no effect on the decompositions.)

Table E.1a: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Women Cohort 35-44

	Source of Variation (% Contribution)															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Outcomes	Educ	μ	η & ν	Emp	ω	Hours	Unearn Inc	ϵ^{ED_s}	$\tilde{\mu}_s$	η_s & ν_s	ω_s	Mar Hist	Sd Mar FE	Mean	SD	*Sum*
Log Earnings	13.43	7.58	36.06	-3.75	1.31	0.59		-0.19	0.56	-0.42	0.19	12.62	0.35	9.59	1.04	68.00
	(2.69)	(1.05)	(3.46)	(1.10)	(.78)	(.73)		(.73)	(.74)	(.72)	(.72)	(2.18)	(.04)	(.06)	(.02)	(5.52)
Log Wages	31.45	44.09	-1.12	-0.27	0.94	-1.09		-0.71	-0.24	-1.15	-0.68	2.17	0.06	2.77	0.45	73.39
	(2.73)	(3.69)	(.81)	(.83)	(1.93)	(.76)		(.81)	(.82)	(.80)	(.85)	(.68)	(.01)	(.03)	(.01)	(5.60)
Log Hours	5.28	0.85	46.61	-5.19	0.73	2.64		0.21	1.06	0.10	0.61	16.67	0.26	6.99	0.66	69.57
	(2.20)	(.75)	(4.16)	(1.27)	(.77)	(.88)		(.77)	(.77)	(.74)	(.75)	(2.77)	(.03)	(.04)	(.01)	(6.11)
Log Fam Earnings	28.97	10.14	22.95	2.02	0.56	3.51		6.55	9.03	4.88	4.22	25.12	0.37	11.31	0.78	117.93
	(4.16)	(1.61)	(2.76)	(1.30)	(1.22)	(1.11)		(1.44)	(1.62)	(1.72)	(1.19)	(3.22)	(.04)	(.05)	(.04)	(8.25)
Log Fam Unearn Inc	4.00	-0.43	5.23	-0.53	0.46	0.29	63.45	1.02	1.37	3.72	0.85	1.81	0.07	8.42	0.53	81.25
	(1.31)	(1.00)	(1.31)	(.97)	(.93)	(.98)	(2.36)	(1.07)	(.99)	(1.17)	(.97)	(.88)	(.01)	(.03)	(.01)	(7.44)
Log Fam Inc	27.19	12.87	9.07	2.16	1.35	2.48	-4.10	6.63	11.65	1.55	4.58	26.48	0.29	11.57	0.59	101.90
	(3.39)	(1.59)	(1.60)	(1.09)	(1.02)	(.90)	(.42)	(1.13)	(1.58)	(1.15)	(1.01)	(2.86)	(.03)	(.04)	(.02)	(6.60)
Log Fam Earnings AE	33.68	11.35	20.94	0.41	0.49	2.86		6.94	9.89	7.16	3.91	7.24	0.18	10.65	0.73	104.87
	(4.03)	(1.63)	(2.85)	(1.18)	(1.17)	(1.10)		(1.50)	(1.68)	(1.88)	(1.18)	(1.67)	(.02)	(.04)	(.03)	(7.86)
Log Fam Unearn Inc AE	4.80	-0.99	7.17	-0.76	-1.05	0.18	48.51	0.60	1.27	1.23	0.55	15.91	0.23	7.75	0.58	77.41
	(1.52)	(.96)	(1.47)	(.95)	(.95)	(.97)	(3.43)	(1.01)	(1.02)	(1.02)	(.96)	(3.39)	(.03)	(.04)	(.01)	(7.78)
Log Fam Inc AE	33.28	14.52	6.58	0.02	1.12	1.96	-4.42	6.64	12.41	2.95	3.83	4.06	0.12	10.90	0.54	82.95
	(3.29)	(1.64)	(1.43)	(.95)	(1.01)	(.87)	(.44)	(1.13)	(1.69)	(1.24)	(1.01)	(.98)	(.01)	(.03)	(.02)	(6.32)

AE = Adult Equivalent. Point estimates are based on the simulation of 100 lives per PSID sample member. Columns 1-12 report the percentage of the variance of each row variable explained by the following factors: (1) education, (2) the wage component μ, (3) the permanent employment component ν and hours component η, (4) the i.i.d shocks to employment status plus variation in initial employment conditional on number of children, marital status, and education, (5) the initial draw and shocks u^{ω} to the autoregressive wage component ω as well as the i.i.d. wage shocks ε^{w}, (6) the initial draw ω^{h}_{25} and the shocks u^{h} to ω^{h} plus the i.i.d. hours shocks ε^{h}, (7) the initial draw and shocks to the autoregressive component of unearned income, (8) the random component ε^{ED_s} of spouse's education, (9) the random component $\tilde{\mu}_s$ of μ_s (10) ν_s and η_s, (11) the random component $\tilde{\omega}^{s}_{0}$ of the initial condition ω^{s}_{0}, shocks to ω^{s} over the marriage, and the i.i.d. shocks to the spouse's wage over the marriage and (12) the contribution of random variation in marriage histories conditional on $[\mu, \eta, \nu, \omega_{25}, EDUC]$. Column 13 reports the sampling error corrected SD of the marriage history fixed effects. Columns 14 and 15 report the mean and standard deviation across individuals of the lifetime sum of each row variable, expressed on an annual basis. Column 16 reports the sum of percentages explained by the factors we consider. Section 6.1 discusses the simulation methodology. Bootstrap standard errors based on 500 draws of the estimation sample are in parentheses.

Table E.1b: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Men Cohort 35-44

	Source of Variation (% Contribution)															
Outcomes	(1) Educ	(2) μ	(3) η & ν	(4) Emp	(5) ω	(6) Hours	(7) Unearn Inc	(8) ϵ^{ED_s}	(9) $\tilde{\mu}_s$	(10) η_s & ν_s	(11) ω_s	(12) Mar Hist	(13) Sd Mar FE	(14) Mean	(15) SD	(16) *Sum*
Log Earnings	40.39	26.51	33.29	2.43	4.98	4.07		1.57	1.53	2.16	1.43	1.50	0.06	11.27	0.72	119.87
	(4.83)	(3.33)	(4.01)	(1.23)	(1.45)	(1.18)		(1.24)	(1.20)	(1.15)	(1.17)	(.34)	(.01)	(.04)	(.04)	(8.32)
Log Wages	38.40	48.83	0.66	0.22	6.53	0.89		-0.06	-0.49	0.61	0.17	0.34	0.02	3.26	0.52	96.10
	(2.40)	(3.37)	(.81)	(.79)	(1.71)	(.82)		(.84)	(.83)	(.79)	(.82)	(.10)	(.00)	(.02)	(.01)	(5.52)
Log Hours	26.78	1.96	75.68	3.50	2.18	14.35		1.81	2.18	2.53	0.75	2.86	0.03	8.05	0.30	134.57
	(9.40)	(2.48)	(4.53)	(2.63)	(2.46)	(3.64)		(2.55)	(2.51)	(2.41)	(2.43)	(.82)	(.01)	(.02)	(.03)	(17.24)
Log Fam Earnings	39.29	27.53	25.68	1.85	6.49	5.30		3.10	2.69	8.15	2.55	6.81	0.12	11.57	0.63	129.45
	(4.26)	(2.93)	(3.47)	(1.19)	(1.39)	(1.15)		(1.20)	(1.24)	(1.40)	(1.16)	(.91)	(.02)	(.03)	(.03)	(8.12)
Log Fam Unearn Inc	3.03	3.12	6.49	0.64	0.23	0.93	72.48	2.34	0.40	3.11	0.80	-2.15	0.04	8.27	0.50	91.41
	(1.44)	(.99)	(1.48)	(.98)	(.97)	(.89)	(2.43)	(1.07)	(.91)	(.96)	(.95)	(.62)	(.01)	(.03)	(.01)	(6.92)
Log Fam Inc	41.55	31.47	11.74	1.20	6.12	4.21	-6.63	3.09	2.99	5.01	2.40	5.51	0.09	11.73	0.52	108.67
	(3.12)	(2.64)	(2.12)	(.92)	(1.26)	(.91)	(.37)	(.97)	(1.01)	(1.09)	(.93)	(.83)	(.01)	(.02)	(.02)	(6.56)
Log Fam Earnings AE	37.66	24.65	22.20	1.29	5.67	3.88		2.02	1.95	7.69	1.53	4.69	0.12	10.85	0.63	113.23
	(4.01)	(2.52)	(3.24)	(1.09)	(1.22)	(1.07)		(1.07)	(1.08)	(1.29)	(1.02)	(.61)	(.01)	(.03)	(.03)	(7.40)
Log Fam Unearn Inc AE	3.39	2.95	6.83	1.01	0.77	1.18	60.41	2.55	0.49	2.39	0.80	6.62	0.15	7.55	0.54	89.39
	(1.44)	(.99)	(1.51)	(.98)	(.93)	(.91)	(2.54)	(1.02)	(.92)	(1.00)	(.92)	(1.99)	(.02)	(.03)	(.01)	(7.03)
Log Fam Inc AE	38.11	26.60	8.91	0.55	5.03	2.74	-6.15	1.79	2.05	4.23	1.12	5.23	0.11	11.02	0.53	90.20
	(3.00)	(2.23)	(1.79)	(.87)	(1.07)	(.90)	(.35)	(.90)	(.88)	(1.02)	(.86)	(.77)	(.01)	(.03)	(.01)	(6.10)

See notes to Table E.1a

Table E.2a: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Women Cohort 45-62

	Source of Variation (% Contribution)															
Outcomes	(1) Educ	(2) μ	(3) η & ν	(4) Emp	(5) ω	(6) Hours	(7) Unearn Inc	(8) ϵ^{ED_s}	(9) $\tilde{\mu}_s$	(10) η_s & ν_s	(11) ω_s	(12) Mar Hist	(13) Sd Mar FE	(14) Mean	(15) SD	(16) *Sum*
Log Earnings	12.14	10.02	56.96	-0.96	1.12	0.94		-0.47	-0.14	-0.53	0.25	3.49	0.20	10.12	1.01	82.82
	(1.60)	(1.11)	(1.66)	(.53)	(.69)	(.59)		(.51)	(.51)	(.53)	(.51)	(.42)	(.01)	(.03)	(.02)	(3.57)
Log Wages	30.77	51.19	0.88	-0.29	4.05	0.23		-0.09	-0.01	-0.71	0.06	0.45	0.04	2.95	0.45	86.54
	(2.08)	(3.53)	(.52)	(.44)	(2.21)	(.47)		(.47)	(.46)	(.47)	(.48)	(.11)	(.00)	(.02)	(.01)	(3.15)
Log Hours	5.44	-0.02	73.58	-1.23	-0.10	3.96		-0.49	0.21	-0.32	0.64	5.24	0.15	7.32	0.61	86.91
	(1.20)	(.60)	(1.70)	(.60)	(.58)	(1.00)		(.58)	(.57)	(.60)	(.59)	(.59)	(.01)	(.02)	(.01)	(4.06)
Log Fam Earnings	21.71	11.41	31.27	-1.13	0.79	0.74		3.36	6.09	2.88	1.56	25.96	0.39	11.47	0.78	104.64
	(2.18)	(1.25)	(1.90)	(.70)	(.77)	(.70)		(.78)	(.96)	(.97)	(.75)	(1.16)	(.02)	(.02)	(.02)	(4.61)
Log Fam Unearn Inc	2.99	0.81	6.33	-0.04	0.45	0.41	62.80	-0.52	1.29	4.00	0.44	0.30	0.08	8.45	0.54	79.28
	(.98)	(.56)	(.90)	(.52)	(.54)	(.55)	(1.88)	(.54)	(.60)	(.85)	(.56)	(.45)	(.01)	(.02)	(.01)	(4.27)
Log Fam Inc	23.13	15.16	13.41	-0.38	1.44	0.35	-4.12	4.90	8.68	0.87	2.63	26.52	0.31	11.71	0.59	92.58
	(1.89)	(1.38)	(1.28)	(.57)	(.71)	(.58)	(.29)	(.68)	(1.02)	(.64)	(.70)	(1.22)	(.01)	(.02)	(.01)	(3.85)
Log Fam Earnings AE	23.74	12.29	31.70	-1.12	0.48	0.49		3.10	6.32	4.67	1.46	10.20	0.22	10.80	0.73	93.33
	(2.13)	(1.29)	(1.82)	(.70)	(.78)	(.68)		(.76)	(.97)	(1.07)	(.76)	(.87)	(.01)	(.02)	(.02)	(4.67)
Log Fam Unearn Inc AE	2.09	0.63	7.45	-0.43	-0.12	0.57	57.24	-0.92	1.07	1.97	-0.02	7.02	0.17	7.78	0.56	76.55
	(.87)	(.53)	(1.00)	(.51)	(.54)	(.55)	(1.87)	(.54)	(.63)	(.72)	(.55)	(1.36)	(.01)	(.02)	(.01)	(4.28)
Log Fam Inc AE	25.80	17.02	13.12	-0.43	1.09	0.43	-4.72	4.47	8.94	2.34	2.24	5.83	0.14	11.04	0.54	76.13
	(1.84)	(1.44)	(1.13)	(.57)	(.74)	(.56)	(.28)	(.65)	(1.05)	(.69)	(.72)	(.69)	(.01)	(.02)	(.01)	(3.93)

See notes to Table E.1a

Table E.2b: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Men Cohort 45-62

	Source of Variation (% Contribution)															
Outcomes	(1) Educ	(2) μ	(3) η & ν	(4) Emp	(5) ω	(6) Hours	(7) Unearn Inc	(8) ϵ^{ED_s}	(9) $\tilde{\mu}_s$	(10) η_s & ν_s	(11) ω_s	(12) Mar Hist	(13) Sd Mar FE	(14) Mean	(15) SD	(16) *Sum*
Log Earnings	25.08	22.18	43.90	0.68	4.66	1.20		0.02	0.13	0.10	-0.62	2.21	0.10	11.25	0.77	99.54
	(2.35)	(2.12)	(2.92)	(.77)	(1.10)	(.80)		(.76)	(.75)	(.78)	(.74)	(.39)	(.01)	(.02)	(.02)	(5.17)
Log Wages	29.55	56.72	-0.77	0.54	9.02	-0.33		-0.14	0.08	-0.21	0.08	0.27	0.03	3.33	0.48	94.80
	(1.82)	(3.27)	(.49)	(.51)	(1.89)	(.49)		(.48)	(.48)	(.46)	(.48)	(.09)	(.00)	(.01)	(.01)	(3.14)
Log Hours	13.32	-1.66	80.90	0.61	1.55	7.58		0.39	0.43	0.21	-1.39	3.79	0.05	7.99	0.37	105.72
	(3.08)	(1.31)	(2.51)	(1.28)	(1.29)	(1.68)		(1.29)	(1.24)	(1.29)	(1.25)	(.73)	(.01)	(.01)	(.02)	(8.58)
Log Fam Earnings	25.89	21.64	34.75	1.24	4.22	1.50		1.34	2.67	6.09	0.54	12.52	0.22	11.65	0.67	112.39
	(2.19)	(1.96)	(2.68)	(.80)	(1.05)	(.84)		(.82)	(.82)	(1.02)	(.79)	(.85)	(.01)	(.02)	(.02)	(5.27)
Log Fam Unearn Inc	2.75	1.14	7.44	0.50	-0.06	0.35	70.12	1.52	0.19	1.75	-0.70	-1.00	0.06	8.33	0.51	83.99
	(.99)	(.65)	(1.32)	(.58)	(.56)	(.57)	(2.02)	(.81)	(.56)	(.66)	(.53)	(.43)	(.01)	(.02)	(.01)	(4.16)
Log Fam Inc	29.95	28.41	16.57	1.19	4.82	1.4	-6.28	2.05	3.20	4.01	1.04	10.97	0.17	11.83	0.53	97.32
	(1.97)	(2.08)	(1.76)	(.60)	(1.01)	(.61)	(.28)	(.61)	(.66)	(.74)	(.60)	(.81)	(.02)	(.02)	(.01)	(3.86)
Log Fam Earnings AE	24.09	21.30	31.65	0.48	3.73	1.14		0.72	2.54	7.34	-0.09	4.59	0.13	10.96	0.65	97.47
	(2.10)	(1.81)	(2.55)	(.71)	(.99)	(.77)		(.76)	(.78)	(.97)	(.72)	(.43)	(.01)	(.02)	(.02)	(4.92)
Log Fam Unearn Inc AE	1.69	1.22	8.59	0.48	0.22	0.46	60.18	1.24	0.27	0.59	-0.53	5.25	0.14	7.63	0.55	79.66
	(.84)	(.67)	(1.32)	(.56)	(.54)	(.58)	(1.92)	(.72)	(.57)	(.62)	(.53)	(1.15)	(.02)	(.02)	(.01)	(4.23)
Log Fam Inc AE	26.50	26.81	12.97	0.21	3.93	0.88	-6.13	1.19	2.98	5.06	0.26	3.20	0.09	11.14	0.52	77.84
	(1.88)	(1.84)	(1.47)	(.55)	(.94)	(.57)	(.24)	(.56)	(.65)	(.71)	(.55)	(.29)	(.00)	(.02)	(.01)	(3.71)

See notes to Table E.1a

Table E.3a: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Women Cohort 67-80

	Source of Variation (% Contribution)															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Outcomes	Educ	μ	η & ν	Emp	ω	Hours	Unearn Inc	ϵ^{ED_s}	$\tilde{\mu}_s$	η_s & ν_s	ω_s	Mar Hist	Sd Mar FE	Mean	SD	*Sum*
Log Earnings	17.91	14.10	52.81	-0.44	2.10	-0.03		-0.21	-0.50	-1.03	0.27	1.46	0.12	10.73	0.97	86.44
	(2.43)	(1.74)	(3.10)	(.69)	(.90)	(.81)		(.66)	(.66)	(.66)	(.70)	(.29)	(.01)	(.07)	(.04)	(4.66)
Log Wages	30.42	55.54	1.99	0.43	7.09	0.12		0.24	-0.59	0.03	0.61	0.11	0.02	3.13	0.46	96.00
	(2.07)	(3.64)	(.65)	(.56)	(2.45)	(.58)		(.53)	(.56)	(.55)	(.53)	(.06)	(.00)	(.02)	(.01)	(3.65)
Log Hours	10.12	1.17	70.86	-1.02	-0.03	1.93		-0.61	-0.28	-1.76	0.04	2.48	0.09	7.72	0.57	82.92
	(2.37)	(.85)	(2.89)	(.88)	(.85)	(1.40)		(.83)	(.83)	(.83)	(.84)	(.45)	(.01)	(.05)	(.03)	(5.83)
Log Fam Earnings	30.46	12.94	32.36	0.45	2.40	2.03		4.28	5.27	4.82	2.90	22.60	0.39	11.73	0.82	120.50
	(2.68)	(1.49)	(2.65)	(.82)	(.97)	(.90)		(.99)	(.96)	(1.05)	(.84)	(1.48)	(.02)	(.04)	(.03)	(5.59)
Log Fam Unearn Inc	1.09	-1.57	6.16	-0.72	-0.02	-1.29	54.41	-0.86	0.90	5.69	-1.15	0.78	0.08	8.19	0.53	63.42
	(.82)	(.64)	(1.10)	(.62)	(.61)	(.61)	(2.50)	(.65)	(.67)	(1.11)	(.62)	(.73)	(.01)	(.02)	(.01)	(4.98)
Log Fam Inc	30.45	17.55	18.00	0.80	2.78	1.44	-4.97	5.09	6.66	2.99	3.36	22.74	0.32	11.90	0.64	106.90
	(2.25)	(1.67)	(1.98)	(.64)	(.89)	(.73)	(.25)	(.84)	(.92)	(.76)	(.72)	(1.48)	(.02)	(.03)	(.02)	(4.61)
Log Fam Earnings AE	30.40	14.51	32.76	0.30	2.44	1.49		4.22	5.52	6.85	2.74	8.25	0.20	11.06	0.76	109.47
	(2.65)	(1.57)	(2.65)	(.84)	(.98)	(.87)		(.98)	(.97)	(1.15)	(.85)	(1.15)	(.02)	(.04)	(.03)	(5.48)
Log Fam Unearn Inc AE	-0.00	-1.06	8.52	-0.97	0.18	-0.74	51.63	-1.10	1.40	3.05	-0.75	6.42	0.17	7.53	0.54	66.59
	(.75)	(.61)	(1.27)	(.61)	(.61)	(.62)	(2.23)	(.67)	(.68)	(.95)	(.60)	(1.57)	(.01)	(.02)	(.01)	(5.08)
Log Fam Inc AE	30.11	20.59	17.93	0.66	3.04	0.87	-5.60	5.00	7.08	5.03	3.11	4.71	0.13	11.24	0.59	92.51
	(2.22)	(1.78)	(1.93)	(.65)	(.93)	(.70)	(.23)	(.80)	(.94)	(.81)	(.71)	(.92)	(.01)	(.03)	(.01)	(4.44)

See notes to Table E.1a

Table E.3b: Decomposition of the Lifetime Variance of Labor Market And Family Income Variables: Men Cohort 67-80

	Source of Variation (% Contribution)															
Outcomes	(1) Educ	(2) μ	(3) η & ν	(4) Emp	(5) ω	(6) Hours	(7) Unearn Inc	(8) ϵ^{ED_s}	(9) $\tilde{\mu}_s$	(10) η_s & ν_s	(11) ω_s	(12) Mar Hist	(13) Sd Mar FE	(14) Mean	(15) SD	(16) *Sum*
Log Earnings	28.47	19.33	56.76	1.47	3.49	1.08		1.42	0.56	1.48	0.68	2.82	0.12	11.23	0.91	117.55
	(3.38)	(1.96)	(2.86)	(.93)	(1.16)	(.92)		(.96)	(.97)	(.90)	(.88)	(.40)	(.01)	(.03)	(.03)	(6.46)
Log Wages	25.44	61.11	-0.67	0.20	10.22	-0.01		-0.34	-0.00	0.11	-0.06	0.34	0.03	3.37	0.47	96.32
	(1.72)	(3.13)	(.60)	(.55)	(2.14)	(.57)		(.58)	(.55)	(.55)	(.55)	(.10)	(.00)	(.01)	(.01)	(3.79)
Log Hours	24.86	1.53	84.91	1.55	0.27	4.16		1.75	0.74	1.85	0.50	4.05	0.07	7.95	0.48	126.17
	(4.51)	(1.33)	(2.80)	(1.31)	(1.34)	(1.43)		(1.36)	(1.37)	(1.29)	(1.24)	(.61)	(.01)	(.02)	(.02)	(9.25)
Log Fam Earnings	31.35	16.02	48.66	1.37	2.51	0.91		2.60	2.18	4.10	1.04	14.37	0.32	11.67	0.84	125.11
	(3.13)	(1.73)	(2.90)	(.95)	(1.11)	(.94)		(1.00)	(1.08)	(1.07)	(.91)	(.92)	(.02)	(.03)	(.03)	(6.51)
Log Fam Unearn Inc	2.73	1.08	12.90	-1.39	-0.17	0.09	59.13	1.34	-0.30	1.85	-0.72	0.19	0.07	8.10	0.50	76.73
	(.93)	(.78)	(2.09)	(.70)	(.70)	(.65)	(2.56)	(.77)	(.66)	(.77)	(.67)	(.78)	(.01)	(.02)	(.01)	(5.17)
Log Fam Inc	32.04	22.94	30.64	1.50	4.19	1.28	-7.24	3.37	3.50	2.79	1.62	14.72	0.26	11.83	0.66	111.34
	(2.50)	(1.90)	(2.41)	(.73)	(1.02)	(.76)	(.35)	(.78)	(.86)	(.84)	(.73)	(.95)	(.01)	(.02)	(.02)	(5.10)
Log Fam Earnings AE	31.28	16.25	46.88	0.91	2.58	0.81		2.47	2.08	6.24	0.91	3.99	0.14	11.03	0.79	114.41
	(2.98)	(1.70)	(2.79)	(.90)	(1.08)	(.89)		(.96)	(1.04)	(1.07)	(.87)	(.55)	(.02)	(.03)	(.02)	(6.20)
Log Fam Unearn Inc AE	2.62	1.47	15.10	-0.97	-0.13	0.49	49.22	0.93	-0.11	0.32	-0.44	8.09	0.18	7.45	0.55	76.59
	(.87)	(.74)	(2.01)	(.67)	(.68)	(.63)	(2.47)	(.69)	(.67)	(.68)	(.64)	(1.43)	(.01)	(.02)	(.01)	(4.92)
Log Fam Inc AE	31.09	23.18	27.19	0.97	4.13	1.14	-7.37	3.06	3.29	5.30	1.37	2.55	0.09	11.19	0.61	95.91
	(2.32)	(1.82)	(2.15)	(.68)	(.98)	(.69)	(.32)	(.73)	(.83)	(.82)	(.70)	(.38)	(.01)	(.02)	(.01)	(4.74)

See notes to Table E.1a

Table E.4: Percentage Contribution of Sorting on Education and Unobserved Wage Components to the Lifetime Variance of Log Family Income Per Adult Equivalent, by Gender and Cohort

	Marital Sorting Variables				*Total Component Contribution*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cohort	Education	μ	ω	All	Education	μ	ω
Panel A: Men							
1935-1944	9.693	2.666	-0.277	12.51	38.113	26.602	5.033
	(1.417)	(0.958)	(0.898)	(1.46)	(2.996)	(2.234)	(1.07)
1945-1962	5.628	2.51	-0.452	10.553	26.505	26.807	3.925
	(0.826)	(0.849)	(0.548)	(0.993)	(1.879)	(1.841)	(0.936)
1967-1980	7.037	3.145	-0.287	10.336	31.087	23.184	4.128
	(0.996)	(0.907)	(0.698)	(1.138)	(2.318)	(1.824)	(0.978)
Panel B: Women							
1935-1944	12.641	2.867	0.05	17.768	33.277	14.522	1.119
	(2.703)	(0.999)	(0.895)	(2.561)	(3.295)	(1.64)	(1.007)
1945-1962	9.623	4.115	-0.496	14.103	25.798	17.016	1.089
	(1.017)	(0.781)	(0.509)	(1.038)	(1.838)	(1.438)	(0.738)
1967-1980	9.351	4.734	0.051	12.869	30.106	20.588	3.042
	(1.016)	(0.874)	(0.614)	(1.068)	(2.22)	(1.784)	(0.928)

Table E.4 displays estimates of the contribution of sorting on education and the unobserved wage components to the variance of several outcomes. The estimates are based on 100 simulations per PSID sample member. Bootstrap standard errors based on 500 draws of the estimation sample are in parentheses.