Marriage Dynamics, Earnings Dynamics, and Lifetime Family Income *

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

October 22, 2024

Abstract

We estimate a statistical model of individual earnings, marriage (with marital sorting), divorce, fertility, and nonlabor income. For the 1935–44, 1945–62, and 1964–74 birth cohorts, we use the model to measure the dynamic responses of earnings and family income to labor market shocks, changes in marital status, education differences and permanent wage differences. The model enables us to isolate the importance of effects operating through marriage probabilities and through spouse characteristics (sorting). We find that gender differences in the responses are large but have declined across cohorts. The decline reflects the increase in the labor supply and wage rates of married women as well as other changes. For each cohort, we also provide gender-specific estimates of the contribution of education, permanent wage, employment and hours heterogeneity, labor market shocks, spouse characteristics, spouse wage shocks, and marital histories to the variance of lifetime family income. For women, own characteristics have become increasingly important in the determination of lifetime family income, while spouse characteristics have become less important. The opposite is true for men. Gender differences in the sources of inequality in lifetime family income have narrowed.

*Yale University, NBER, and IZA. Email: joseph.altonji@yale.edu. **Yale University. Email: william.giraldo@yale.edu. ***Federal Reserve Board. Email: ivan.vidangos@frb.gov. Our brilliant and kind co-author, Disa Hynsjö, passed away in July 2021 after a sudden illness. We mourn her passing. Our research has been supported by the Cowles Foundation, the Tobin Center for Economic Policy, and the Economic Growth Center, Yale University (Altonji). This work was supported in part by the facilities and staff of the Yale University Faculty of Arts and Sciences High Performance Computing Center, and by the National Science Foundation under grant #CNS 08-21132 that partially funded acquisition of the facilities. We thank the editor, the referees, Paula Calvo, Mariacristina De Nardi, Luigi Guiso, Yujung Hwang, Costas Meghir, Luigi Pistaferri, Robert Pollack, Jean Marc Robin, Kjell Salvanes, Seth Zimmerman, and participants in seminars at CEPR/Stockholm University, Cornell, the Federal Reserve Bank of Minnesota, Stanford, U. of Michigan, UCL, Western University, U. of Wisconsin, and conferences organized by CREAM, the Econometric Society, Johns Hopkins, SED, SOLE, and SoCCAM for helpful comments. We also thank Serena Goldberg, Mona Mahadevan, Lucas Marron, Eleri Phillips, and Owen Rask for excellent research assistance. The views expressed in the paper are our own and do not necessarily represent the views of the Federal Reserve Board, Yale University, NBER, IZA, or other members of their staffs. We are responsible for the remaining shortcomings of the paper.

1 Introduction

Understanding the dynamics and distribution of family income during adulthood is key to understanding the distribution of material well-being. To understand family income, one must examine not only the determinants of personal earnings, but also those that govern marital decisions and the earnings of one's spouse. For example, education affects income by altering the path of own work hours, wage rates, and, thus, own earnings. But it also influences one's family income by affecting the probability of finding a spouse and the characteristics of that spouse. Similarly, a divorce shock not only influences own labor supply but also has an obvious effect on access to a spouse's earnings. It follows that gender differences in the processes that drive earnings while single and while married will lead to gender differences in what factors matter most in determining lifetime family income. For example, if women work much less than men while married, then unemployment shocks will be less important for women, while marital sorting will be more important.

In this paper, we use an econometric model of earnings, marriage, marital sorting, fertility, and unearned income to study the dynamics and the distribution of family income by gender and birth cohort, with a special focus on how these are shaped by marriage and assortative mating. In the model, individual earnings depend on gender and marital status and incorporate multiple sources of permanent heterogeneity and transitory shocks. Both permanent personal characteristics and labor market shocks influence the probability of entering a marriage. The divorce probability depends on fixed and time-varying characteristics of both marriage partners. We incorporate assortative mating by estimating the effects of an individual's characteristics on the distribution of the characteristics of marriage partners that matter for earnings or marital stability. These include education and unobserved heterogeneity components that influence wages, employment status, and hours.

Crucially, we allow intercepts and some slope parameters in key equations to vary with birth year. As Goldin (2006, 2021), Lundberg and Pollak (2007), Ruggles (2015), Blau and Winkler (2017), Juhn and McCue (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 notably, especially among married women, while for men it has fallen to some degree. Female education levels rose dramatically relative to men, and the gender gap in wage levels narrowed. Accordingly, the female share of family earnings among married couples has risen substantially. At the same time, marriage and fertility rates have fallen, meaning that the differences in labor market behavior of married men and women matter less for income over a lifetime than they did earlier. The upshot is that the economic roles of men and women have converged to some extent, although large differences remain.

These changes are reflected in our estimated model.

We estimate our model using panel data from the 1970-2019 waves of the Panel Study of Income Dynamics (PSID). We then use model simulations to study and compare three broad birth cohorts: an "early" cohort consisting of individuals born between 1935 and 1944 (inclusive), the baby boom cohort (1945-1962), and a "late" cohort (1964-1974). Throughout the paper, "married" includes both cohabiting and legally married couples.

Our first set of results concerns the dynamic response of own log earnings, log family earnings, and log family income per adult equivalent (which we call y_ae_{it}, where i and t are person and year subscripts) to a variety of shocks.[1] These include unemployment shocks, wage shocks, and divorce shocks.

We find large differences between men and women in the effects of own unemployment, wage shocks, divorce, marriage, and shocks to spouse's earnings on the path of family income. But we also find that these differences have declined substantially between the early, baby boom, and late cohorts that we study. To illustrate, consider the effects of a divorce shock. For women in the early cohort, a divorce at age 34 leads to an initial drop in y_ae_{it} of -0.75 log points, followed by a slow partial recovery to an effect of -0.12 log points by age 55 (relative to the baseline). For women in the late cohort the initial drop is -0.69. For men, a divorce leads to a small *increase* of 0.05 log points in y_ae_{it} for the early cohort but a drop of -0.16 for the late cohort. Thus the gender differential in the mean effect of a divorce on y_ae_{it} has narrowed from 0.80 to 0.53 log points between the early and late cohorts. This change reflects in large part the growing importance of women's earnings for married couples.

For an unemployment shock, the effect on own earnings for married women in the early cohort is -0.08 log points, with a full recovery in 5 years. The negative effect more than triples for the late cohort, to -0.26. The growth in the earnings response is mirrored in an increase in the response of y_ae_{it} from -0.02 to -0.08. For married men, the negative effect of an unemployment shock on own earnings is -0.25 for the early cohort and -0.44 for the late cohort. However, the increase in the absolute magnitude of the effect on y_ae_{it} for men across these two cohorts is only 0.07 log points, despite the large (0.19 log point) increase in the size of the earnings effect. For a wage shock, the effect on family income is also much stronger for men than for women in the early cohort, but the gap narrows substantially across cohorts. The cross-cohort changes for women relative to men reflect the growing importance of women's earnings for family income.

[1] Using a per-adult-equivalent measure accounts for having to spread family resources over more than one person, and also accounts for returns to scale in the household and for children's lower demand of resources. Specifically, we use the OECD's equivalence scale (AE), which equals 1 + 0.7 (if the person is married) + 0.5×(Number of children between 0 and 18 years of age).

Our second set of results concerns the gender- and cohort-specific effects of differences in education and the permanent component of wage rates on the levels and evolution of log earnings and y_ae_{it} between ages 25 and 55. Because we model both individual earnings and marriage, as well as marital sorting, we can also measure the degree to which the lifecycle effects work by influencing whom one marries, which we refer to as the "sorting channel," and by influencing the probabilities of marriage and divorce, which we refer to as the "marriage channel." The college-high school differential in earnings and y_ae_{it} is large for both men and women, but the contribution of marital sorting to the differential in family income y_ae_{it} is much larger for women. Thus, positive assortative mating is central to the economic return to education for women, as Goldin (1990) and others have found. But we also find important changes across cohorts. First, for women the average (across ages 25-55) of the education differential in y_ae_{it} grew relative to the corresponding average for the education differential for own earnings. Second, the contribution of marital sorting to the education differential declines by a small amount for women across cohorts, as women marry less and work more, while the marriage channel grows in importance. Third, for men the education differential in earnings increases substantially across cohorts, primarily because of an increased education gap in work hours prior to age 50. But the ratio of the education differential in y_ae_{it} to the education differential in earnings fell for men from 0.85 to 0.72, which is the opposite of what happened for women. Furthermore, across generations, the contribution of the marriage channel and the sorting channel to the education differential grows in importance for men relative to women.

Regarding permanent wages, we find that the effect of a one-standard-deviation increase in the permanent wage component on women's earnings grows from an average (across ages 25-55) of 0.34 log points for the early cohort to 0.44 for the late cohort, reducing the gap with men. For women the effect on y_ae_{it} increases from 0.21 to 0.27, a similar percentage increase, also reducing the gender gap. For women the sorting channel accounts for about one-third of the effect on y_ae_{it} in the early cohort and about one-sixth for the late cohort. For men, the contribution of sorting is smaller but increases across cohorts. To the best of our knowledge, we are the first to quantify the role of marriage probabilities and marital sorting in determining the importance of education and permanent wages for family income over the lifecycle.

In our final set of results we quantify the sources of lifetime inequality. Specifically, we provide gender- and cohort-specific decompositions of the variance (across individuals) in the average y_ae_{it} between ages 25 and 55 (we denote these lifetime averages by y_ae_i). The sources of variation consist of: education; permanent unobserved heterogeneity in wages, labor force status, and hours; employment shocks, hours shocks, and wage shocks; random variation in marriage partner characteristics; partner wage shocks; and random variation in marital status over a lifetime.[2] To the best of our knowledge, we are the first to provide such a full decomposition. We also use counterfactual simulations to assess the overall contribution of marital sorting to inequality.

The overarching theme of our variance decomposition results is that while whether one marries and whom one marries is more important for lifetime average family income y_ae_i for women, the gender difference has narrowed significantly across cohorts. We next summarize the key results from the variance decompositions.

First, education accounts for much of the variance of y_ae_i across individuals for both men and women, but its contribution has declined across cohorts. For the early cohort, the contribution is 38% for men and 35.3% for women, whereas for the late cohort, the values are 29.9% and 24.8%. These contributions capture all of the channels through which education affects lifetime family income in the model, not just through own earnings. The gender difference in the relative importance of education for own earnings versus y_ae_i narrowed, reflecting the rising female share of y_ae_i among married couples and the decline in marriage.

Second, the permanent wage component plays a larger role for men than for women, but the gap has narrowed across cohorts. For women, the variance contribution of the permanent wage component rose from 13.8% for the early cohort to 21.6% for the late cohort. For men, the variance contribution stayed flat at 26.4%. The relative increase in the contribution of the permanent wage for women reflects at least in part the increased labor force participation of women and the corresponding larger contribution of women's earnings to overall family income in more recent cohorts.

Third, the combined contribution of the permanent components of employment and of hours conditional on employment has grown. For women, the contribution rose from 6.3% for the early cohort to 13.1% for the late cohort. For men, the increase is from 5.2% to 20.5%. We constrain the variance parameters to be constant across cohorts, so the increase for women likely results from their increased hours and wage rates conditional on participation 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 raises the sensitivity of employment to the permanent employment component.

Fourth, the contributions of the shocks to wages and hours are relatively small, in large part because the effects of these shocks are sufficiently transitory that they fade over the course of a lifetime. However, the relative importance of wage shocks and the permanent wage component are somewhat sensitive to estimates of the persistence of wage shocks.

[2] The family income distribution also depends on spousal employment and hours shocks, fertility shocks, and nonlinearities and interactions. We lump these all into a separate category.

Surprisingly, the contribution of employment shocks to the lifetime variance of y_ae_i is negative, reflecting nonlinearities in the model.

Fifth, we find substantial gender convergence in the importance of random variation (conditional on one's own characteristics) 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 spouse's permanent components of employment and hours declined from 27.4% for the early cohort to 19.5% for the late cohort. For men, the corresponding values are 0.4% and 11.7%, indicating growth in the importance of randomness in matching, but from a much lower starting point.

Sixth, the contribution of marital sorting on education and on the permanent and transitory wage components to the variance of lifetime family income fell by a large amount across cohorts for women, closing most of the gender gap. The combined contribution decreased from 21% for women in the early cohort to 12.8% for those in the late cohort. The corresponding values for men are 9.2% and 10%.

Finally, we provide the first estimates of the importance of random variation in marital histories (conditional on permanent characteristics). It accounts for 3.3% of the variance in y_ae_i for women in the early cohort and 7.9% for women in the late cohort. For men, the contribution has fallen slightly across cohorts, from 3.4% for the early cohort to just 2.7% in the late cohort. Overall, variation in marital histories matters a little more for women than for men.

Overall, the variance decompositions indicate that as gender roles have changed, with women's labor force participation increasing (along with marriage and fertility rates declining), 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. The opposite is true for men. This has contributed to a narrowing of gender differences in the sources of inequality in lifetime family income. In a follow-up paper, Altonji, Giraldo-Páez, Hynsjö, and Vidangos (2024), we use the model, data, and variance decomposition methodology in the present paper to quantify the sources of inequality at different points in the lifecycle rather than lifetime averages.[3] The age-specific variance decompositions of earnings and y_ae_{it} also exhibit large gender differences that have declined across cohorts.

Our paper builds on several literatures. First, there is of course 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

[3]The text of our companion paper draws heavily on the descriptions of the model, data, fit, and decomposition methodology in the present paper, often verbatim.

elasticity include Blau and Kahn (2007) and Heim (2007), who study change over time. Juhn and McCue (2016, 2017) consider the effects of marriage and children on the earnings gap across cohorts. The large literature on the effects of children on employment, hours, and wages includes recent papers by Kuziemko et al. (2018), Kleven et al. (2019), and Andersen and Nix (2022). Blau and Kahn (2017) survey the literature on sources of gender differences in labor market outcomes, including the role of marriage, children, and workforce interruptions. Other papers study the effects of unemployment shocks for future wages and employment.[4] The equations of our earnings model draw on this vast literature but do not advance it. Our empirical model of marriage, divorce, and marital sorting is also loosely motivated by a large literature surveyed by Browning, Chiappori, and Weiss (2014) and Chiappori (2020).[5] Our contribution is to combine the equations for earnings, marriage, and sorting into a dynamic model of lifetime earnings and family income that can be simulated. The model permits us to study the effects of shocks and the sources of lifetime inequality by gender and cohort and to explore mechanisms.[6]

As we noted earlier, our focus on cohort differences is motivated by the vast literature on long-term changes in female labor supply, wages, fertility, and marriage that we previously mentioned. Several papers, including Fernandez and Rogerson (2001), Fernandez, Guner, and Knowles (2005), Hryshko, Juhn, and McCue (2017), Eika, Mogstad, and Zafar (2019), and Chiappori et al. (2020) study the link between trends in assortative mating and trends in inequality. This work focuses primarily on annual income. Eckstein, Keane, and Lifshitz (2019) use a structural model to explain cross-cohort trends in employment, education, marriage patterns, and fertility. Heathcoate, Storesletten, and Violante (2010) use a two-person household model with assortative mating fixed and show that changes in the wage structure

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

[5]This literature includes the seminal contributions of Becker (1973, 1974) and subsequent papers such as Choo and Siow (2006). Wong (2003) and Gousse, Jacquemet, and Robin (2017) are notable examples from a literature that considers sorting and marriage in the presence of search costs.

[6]Other papers study multivariate processes for earnings, with equations for employment, hours, and wage rates. Within this strand of the literature, our approach is most closely related to that of Altonji, Smith, and Vidangos (2013). They focus exclusively on the earnings process of male heads of household and consider job mobility. We abstract from job mobility, but in contrast to most of the univariate and multivariate literature, we consider women as well as men and incorporate marriage, marital sorting, fertility, and nonlabor income. These additions enable us to estimate impulse response functions and variance decompositions for family income, not just individual earnings, and to isolate the role of the sorting and marriage channels. A large but more distant literature estimates univariate processes for earnings and/or family income and considers implications for inequality at various ages, over the lifecycle, or over time. 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 (2023) for an overview of the multivariate and univariate literatures, with detailed references.

and dynamics can explain changes in the cross-sectional distributions of individual hours worked, household earnings, and household consumption. Our model is statistical/reduced form rather than structural, but we consider sorting on *all* of the variables that matter (in our model) for future earnings and nonlabor income, and we also allow assortative mating to change over time. The payoff is that we can quantify cohort and gender differences in the sources of lifetime inequality and the role played by the sorting channel and the marriage channel.[7]

The remainder of the paper is organized as follows. Section 2 discusses the data. Section 3 discusses the model, describes the estimation methodology, 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 dynamic responses of key variables to exogenous shocks. Section 6 considers the effects of differences in 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

2.1 The Panel Study of Income Dynamics (PSID) Sample

We use the 1970–2019 waves of the PSID to assemble a panel of sample members and their spouses.[8] Sample members of the PSID (and their descendants) are surveyed every wave, allowing us to study family income dynamics over people's lives. Spouses enter the PSID by legally marrying or cohabiting with a PSID sample member for more than a year. They are not sample members. Spouses who have separated from sample members are no longer surveyed. The data refer to the calendar years 1969–2018.

We restrict the analysis to stratified random sample (SRC) members who are not Black.[9] Our analysis focuses on sample members who are aged 25 to 61, inclusive, as well as their spouses. We start at age 25 because many sample members younger than 25 are not heads of household or spouses, and many key variables are not collected for non-head singles.[10]

[7] Our analysis of responses to labor market shocks is also relevant for a recent literature in macroeconomics that has begun to account for gender differences and the role of the family in studying aggregate fluctuations, including, for example, Mankart and Oikonomou (2017), Borella, De Nardi, and Yang (2018), Albanesi (2020), and Fukui, Nakamura, and Steinsson (2023). We focus on idiosyncratic rather than aggregate risk.

[8] We start in 1970 because several key variables are bracketed or not available in the 1968 and 1969 waves.

[9] We are studying racial differences in family income dynamics in ongoing work.

[10] The vast majority of individuals younger than 25 who are not heads of household are children or stepchildren of the heads.

Consequently, our results apply to individuals who are single heads of household or married (or cohabiting) at age 25.[11] For the most part, we exclude observations if the potential experience of the sample member or the spouse is greater than 40 or they are older than 61 because we do not model retirement as a distinct labor force state.

In some cases, we deviate from our principal sample. Because of sample size considerations, we use data for ages 23-27 when estimating some models of initial conditions at age 25. We also do not restrict the age of the spouse when estimating the marriage and age matching equations. Observations for a given person-year are used if the person has valid data on education. The number of observations used in estimation varies across equations, but 8,250 sample members play a role in our simulations.

2.2 Key Variables

We discuss the most important issues in constructing our key variables here. Appendix A contains detailed, complete information on the data and its construction.

The subscript i denotes the PSID sample member and the subscript t denotes calendar year; below, these are sometimes suppressed. The subscript s indicates that a variable refers to a spouse. 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 the econometric model, we use a * superscript to distinguish the measured value from its true value. We use the personal consumption expenditures implicit price deflator to convert all monetary variables to 2012 dollars.

In constructing our analysis file, we navigated changes in the questions and structure of the PSID to arrive at consistent variable definitions. In 1997, the PSID switched from an annual to a biennial interview schedule. This meant that a significant amount of sample member information that is available on a yearly basis before 1997 is available only biennially in the subsequent years. Fortunately, for many of our key variables post-1997, including annual earnings, hours, and unemployment, the PSID began asking two-year retrospective questions in addition to the typical one-year retrospective questions. We made use of these two-year retrospective questions to produce a panel with annual observations.

Education ($EDUC_i$) is years of education, which we measure by its average when multiple reports are available. Potential experience, PE_{it}, is $age_{it} - max(EDUC_i, 9) - 6$. We use B_i

[11] After children set up their own household, they are classified as heads or wives even if they move back in with their parents. An alternative would be to start at an earlier age, treat "single, has not left home" as a state variable, and account for the fact that some labor market variables are not available for non-head single adults. Starting at an earlier age and restricting the sample to heads and wives will lead to bias because the marriage rate is overstated in this sample. Note that, until recently, for married or cohabiting couples the PSID (which started in 1968) almost always classifies the male as the "head" and the female as the "wife."

to denote sample member i's year of birth.

The key components of our measure of family income are earnings, hours, hourly wages, labor market status, and nonlabor income. We construct our earnings, labor market status, and hours variables directly from one-year and two-year retrospective questions in the PSID. The hours measure $HOURS^*_{it}$ is annual hours worked in all jobs. We impose a floor of 200 when we use the variable in the log hours model to reduce the influence of distinctions between low values of the hours level (including zero hours) that are not economically significant.

The (measured) hourly wage $WAGE^*_{it}$ is annual earnings divided by annual hours, before the floor of 200 is imposed on hours. When this value is missing, either because annual earnings are not reported or annual hours are zero, we impute values for the wage. For this imputation, we employ the response to a PSID question regarding the individual's reported hourly wage rate at the time of the survey, if it is available, or demographic information, if it is not.[12]

Measured earnings $EARN^*_{it}$ is the individual's annual earnings in all jobs. We impose a floor of $1,300 prior to taking logs but *after* creating the wage rate. The floor corresponds to the earnings from a minimum wage of $6.50 and the hours minimum of 200 that we employ. We do not subsequently adjust PSID earnings to reflect the application of the wage floor. As a result, $ln(EARN^*_{it})$ is sometimes below the sum of the logs of our PSID wage and hours measures.[13] We do not topcode $EARN^*_{it}$. Note that $EARN^*_{it}$ is only used to evaluate fit. It does not play a direct role in estimation of the model, in the impulse response analysis, or in the variance decompositions.

Our mutually exclusive labor force status measures refer to the calendar year. Not working (N_{it}) is 1 if the person did not work positive hours in the year and 0 otherwise. Unemployment (U_{it}) is 1 if the person worked positive hours during the year ($N_{it} = 0$) and reported positive weeks of unemployment during the year. Employment (E_{it}) is 1 if $N_{it} = 0$ and the person reported no weeks of unemployment. The small set of person-year observations for individuals who experience unemployment but work zero hours are classified as out of the labor force rather than unemployed. We denote participation as P_{it},

[12]To be more specific, we filled in missing data on $wage^*_{it}$, the log of $WAGE^*_{it}$, with $wage^*_{1it}$, which is the prediction from a regression of $wage^*_{it}$ on the log reported wage rate at the survey, ($REP\_WAGE^*_{it}$), $EDUC_i$ and other explanatory variables, all fully interacted with gender. If the reported wage is also missing, we set $wage^*_{it}$ to $wage^*_{2it}$, where $wage^*_{2it}$ is the predicted value from a gender-specific regression of $wage^*_{it}$ on the explanatory variables only.

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

where $P_{it} = 1 - N_{it} = E_{it} + U_{it}$. Wives were not asked whether they had any hours of unemployment in the previous year prior to the 1975 survey.

Nonlabor income NLY_{it} is household taxable income plus transfers received minus earned income. 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. We impose a floor of \$500 before taking logs.

Family income Y_{it} is the head plus the spouse's taxable income plus transfers received. We impose a floor of \$2,000. Family income per Adult Equivalent, Y_AE_{it}, is Y_{it}/AE_{it}, where AE_{it} is the number of adult equivalents in the household. The latter measure accounts for the fact that bigger families must spread out a given set of resources across more people, while also adjusting for children using fewer resources and returns to scale in the home. We use the OECD's equivalence scale and define AE_{it} as $1 + .7MAR_{it} + .5 \times$ (Number of children between 0 and 18 years of age).

The marital status dummy variable MAR_{it} is 1 if the sample member is legally married or has been cohabiting for a year or more. Throughout the paper, "married" includes cohabitors. We construct MAR_{it} and marriage duration in years ($MDUR_{it}$) using PSID questions that refer to the survey date, the PSID's Marital History File, and move-in/move-out data on household composition.

We construct a birth indicator and measures of the number of children of each age under 18 using the PSID Childbirth and Adoption File. For the most part, we aggregate counts of children into number of children between 0 and 5 ($CH05_{it}$), 6 and 12 ($CH612_{it}$), and 13 and 18 ($CH1318_{it}$).

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 the possibility that differences in the data play some role in differences in dynamics. Appendix Table A.1 reports summary statistics by gender and cohort for the key variables in the model for observations on individuals between ages 25 and 61. The effective sample for estimation may vary due to missing data and additional sample selection rules for each portion of the model.

3 A Model of Earnings, Marriage, and Family Income

Our model has six parts. The first specifies the initial conditions for the model: 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 individual earnings, with models for labor force status, annual work hours, and wage rates, which together determine earnings. The third is for nonlabor income. The fourth part of the model concerns marital status transitions. Only married individuals have spouse's earnings included as part of family income. The fifth part concerns marital sorting, which determines spouse's education, age, initial employment status, and the permanent (and transitory) wage component. The sixth part determines fertility after age 25.

Each of these parts of the model contains multiple individual equations. For each of the individual equations, different variables are included as explanatory (right-hand side) variables. Polynomial forms of variables and interactions across variables are also included. To guide the model selection process, we used a mix of AIC, joint significance, or individual statistical significance.[14] Altogether, the model contains 49 equations and 957 parameters to be estimated.

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

There are far too many equations and parameters to allow for a full discussion in the text. Appendix Tables B.1a and B.1b present a summary of most of the equations.[15] These summary tables are intended to provide an overview of the model; they do not fully capture the model's richness.

In the rest of this section, we write out all the estimating equations for each of the models, list the variables, explain the estimation procedures, and very selectively discuss how the model estimates compare to other findings in the literature.[16] The estimation method varies

[14] For the sake of symmetry, in some cases we include variables in the male (female) equation that are not significant or worsen the AIC because statistical tests and/or AIC suggest the inclusion of the variables for females (males).

[15] They do not include the model for the sample member's initial conditions, but that part of the model is explained below.

[16] The tables in Appendix B report all parameter estimates and the table notes provide details about the

across equations; for some equations we used OLS, probit, or multinomial logit, while for others we used IV to address endogeneity. The standard errors of model parameter estimates are based on the asymptotic formula and are clustered by sample member, although we use the bootstrap for a few parameters for which the asymptotic formula is impractical.

3.1 Initial Conditions at Age 25

The model starts at age 25. Gender, birth cohort, and education are exogenous. For each gender-cohort-education combination, we estimate the conditional probability of each combination 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. In constructing the conditional probabilities, we aggregate education into a "low" group (up to twelve years of education) and "high" group (more than twelve years). This results in four gender-education combinations. The cohort groupings are for birth years 1935–44, 1945–53, 1954–62, and 1963–74.[17] Thus we have a total of 20 gender-cohort-education combinations.[18]

Finally, we need to draw the initial ages of the children. To do this, for each possible value of number of children at age 25, we estimate the joint probability of each of the possible combinations of ages of the children. This joint probability was calculated across all PSID sample members at age 25; that is, it was unconditional with regards to gender, cohort, or education.

3.2 Earnings

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 ($N_{it} = 0$). We abstract from modeling job mobility and the presence of job-specific wage and hours components despite their empirical importance.[19]

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estimation procedure. Appendix B also contains more details about the models and their estimation.

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

[18] Because unemployment data are missing for many women before 1974, and because many individuals in the first cohort grouping are not observed around age 25 (they were much older than that by the time the PSID began), we adopt various procedures to impute these initial conditions for sample members before estimating the joint distributions. See Appendix B.2.

[19] See, for example, Abowd, Kramarz, and Margolis (1999), Card, Heining, Kline (2013), and Altonji, Smith, and Vidangos (2013).

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. The log wage is determined by the following equations:

$$\begin{aligned}
wage_{it} &= P_{it} \cdot wage^{lat}_{it} && (1)\\
wage^{lat}_{it} &= X^w_{it}\gamma^w_X + \mu_i + \omega_{it} + \varepsilon^w_{it} && (2)\\
\omega_{it} &= \gamma^\omega_0 + \rho^\omega \omega_{i,t-1} + \gamma^\omega_U U_{i,t-1} + u^\omega_{it} \text{ if } age_{it} > 25 && (3)\\
\omega_{it} &= \omega_{i25} \text{ if } age_{it} = 25 \text{ ; } \omega_{i25} \sim N(0, \sigma^2_{\omega 25})\\
\mu_i &\sim N\left(0, \sigma^2_\mu\right) \text{ ; } u^\omega_{it} \sim N\left(0, \sigma^2_{u^\omega}\right) \text{ ; } \varepsilon^w_{it} \sim N\left(0, \sigma^2_{\varepsilon^w}\right).
\end{aligned}$$

Equation (1) says that the $wage_{it}$, equals the "latent wage" $wage^{lat}_{it}$ for people participating in the labor market (i.e. $P_{it} = 1$). For those not participating (recall this means they work zero hours at time t), $wage^{lat}_{it}$ 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.

The latent wage $wage^{lat}_{it}$ depends on a set of regressors X^w_{it}, a permanent wage component μ_i, an autoregressive wage component ω_{it}, and the i.i.d. shock ε^w_{it}. The vector X^w_{it} contains marital status MAR_{it}; a cubic time trend; education $EDUC_i$; potential experience PE_{it}, PE^2_{it}, and PE^3_{it}; the interaction between $EDUC_i$ and both PE_{it} and PE^2_{it}; and the vector CH_{it} containing counts of children aged 0-5, 6-12, and 13-18. For men, X^w_{it} also includes $CH18+$, an indicator for having a child over age 18. For women only, it also contains the square of birth cohort B_i; the interaction between $CH05_{it}$ and B_i; and interactions between MAR_{it} and B_i and B^2_i. Also for women only, X^w_{it} includes the labor force status vector $LFS_{i,t-1}$, which consists of $P_{i,t-1}, P_{i,t-2}, P_{i,t-3}, U_{i,t-1}$, and $U_{i,t-2}$. Because $LFS_{i,t-1}$, the child variables, and the marital status variables may be correlated with μ_i, we instrument them—and their interactions with cohort—using deviations from their i-specific means. The deviations from i-specific means could be correlated with the transitory shocks, which we do not address.[20]

Equation (3) states that 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}. For women, who are more likely to have long spells of nonparticipation, we exclude $U_{i,t-1}$ from (3) because in preliminary work we found that

[20] 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 regressions for $P_{i,t-1}$, $P_{i,t-2}$, $P_{i,t-3}$, $U_{i,t-1}$, and $U_{i,t-2}$ estimated using women between ages 23 and 27.

including it in the model implied too large a penalty from nonparticipation. Instead, we include $LFS_{i,t-1}$ in (2).[21] We allow for a separate i.i.d measurement error component in the observed wage (not shown).

Appendix Table B.2a columns 1 and 2 report 2SLS estimates of (2) for men and women, respectively. The marital premium is 0.051 (0.010) for men. For women, the premium is negative for the early cohorts but rises slowly with birth cohort. It is -0.066 for the 1935 cohort, essentially 0 for the 1960 cohort, and 0.018 for the 1974 cohort.[22]

Wages are substantially lower for women with children, and the penalty increases with birth cohort. We find a small positive effect of children on wages for men, which is consistent with most studies (Yu and Hara, 2021). For women the coefficients on the three lags of participation sum to 0.289, suggesting an important role for recent labor market experience. Lags of unemployment enter negatively.

Appendix Table B.2b reports the parameters for the ω_{it} process as well as the variances of μ_i, ε^w_{it}, and measurement error.[23] For men, the effects of unemployment $U_{i,t-1}$ in (3) on the wage is -0.109, in keeping with other studies that distinguished hours effects and wage effects. The value of $\hat{\rho}_\omega$ is 0.810 (.027) for men and 0.770 (0.044) for women, which suggests less persistence of shocks than some other studies surveyed in Altonji et al (2023) have found. Therefore, in our results section we test the sensitivity of our findings to restricting ρ_w to 0.9 for both genders when estimating the wage model. The standard deviation of the AR(1) innovations, $\hat{\sigma}_{u^\omega}$, is 0.184 (0.007) for men and 0.186 (0.010) for women. The estimate of σ_μ is 0.349 (0.011) for men and 0.332 (0.013) for women, so permanent heterogeneity is substantial.

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

We model E_{it}, U_{it}, N_{it} using a dynamic multinomial logit model with normally distributed random effects, treating N_{it} (nonparticipation) as the reference category. Let the latent

[21] We estimate (3) 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 (in the male case) as instrumental variables. We use a method of moments procedure to estimate to σ_μ, σ_{ε^w}, σ_{u^w}, and $var(me^*_{it})$. It involves the use of the survey wage measure to identify $var(me^*_{it})$. See Appendix B.3.

[22] Our finding for men is consistent with most of the literature, which finds a positive marital wage premium even after accounting for selection into marriage. Our finding for women is consistent with Juhn and McCue's (2016) finding using fixed effects methods of a negative marriage premium that has turned positive for more recent cohorts. They argue that the latter result is driven primarily by college-educated women without children. We did not incorporate these interactions.

[23] The regression coefficients and variance parameters of (3) are estimated using a combination of 2SLS (to account for endogeneity of $P_{i,t-1}$ and $U_{i,t-1}$ in the equation for men, for measurement error, and for the presence of μ_i) and the methods of moments. See Appendix B.3.

variables V_{it}^E and V_{it}^U denote the value of employment and of unemployment in the current period relative to the value of nonparticipation. The equations for V_{it}^E and V_{it}^U are

$$V_{it}^E = X_{it}^E \gamma_X^E + \nu_i + \xi_t^E - \xi_{it}^N \tag{4}$$

$$V_{it}^U = X_{it}^U \gamma_X^U + \nu_i + \xi_t^U - \xi_{it}^N \tag{5}$$

The vectors X_{it}^E and X_{it}^U contain a cubic time trend, $EDUC_i$, and a cubic in PE_{it}, $wage_{it}^*$, and $wage_{sit}^*$ for those who are married. They also include MAR_{it}, the vector CH_{it} containing counts of children aged 0-5, 6-12, and 13-18, B_i^2, and B_i^3. We include $CH_{it} \cdot B_i$ for men. The vectors X_{it}^E and X_{it}^U also contain interactions of $EDUC_i$ with a cubic in birth cohort. For women, most variables are also interacted with MAR_{it}, including the time trend and birth cohort.[24] Finally, the model contains 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. We refer to ν_i as the permanent employment component.

Note that the model includes the lags $E_{i,t-1}$ and $U_{i,t-1}$ as well as the normally distributed random effect ν_i. In most cases we do not observe initial conditions. As a result, initial conditions bias is likely to lead to an overstatement of state dependence and an understatement of σ_ν^2, which we do not directly address. Instead, we examine the sensitivity of our impulse response estimates and variance decompositions to restricting the estimate of σ_ν^2 to 1.5 times the unrestricted estimate. We do not address potential correlation between MAR_{it}, CH_{it} and the wage rates with ν_i and the labor force status shocks. The presence of lags of E_{it} and U_{it} in the marital transition equations imply such a correlation between MAR_{it} and ν_i.

The multinomial logit coefficients are presented in Appendix Table B.3. We find strong state dependence and substantial unobserved heterogeneity. We find small positive own wage effects and small negative effects of spouse's wage. 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 on employment, which is consistent with a vast literature. Appendix Figures C.1-C.2 show the age profiles of the predicted employment, unemployment, and nonparticipation rates by age and birth cohort, not holding other variables fixed. The nonparticipation rate for men does not change much between the early and baby boom cohorts, but increases by about 0.03 in the late cohort. For women, nonparticipation decreases slightly between the early and baby boom cohorts and substantially between the baby boom and late cohorts.

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

3.2.3 Log Annual Hours

The model for the log of hours conditional on working positive hours is reported in Appendix Tables B.4a and B.4b. It is

$$hours^*_{it} = X^h_{it}\gamma^h_X + e^h_{it} \text{ if } P_{it} = 1.$$

The vector X^h_{it} includes a cubic time trend, $EDUC_i$, and a cubic in potential experience PE_{it}. For both men and women, we pool singles and married but include Mar_{it}. The equations include U_{it}, which picks up the effect of hours lost to unemployment, and its interaction with a quadratic in B_i. We include $EDUC_i$ and its interaction with a quadratic in potential experience. The equation also includes $wage^*_{it}$. For women only, we include children CH_{it}, allow the effects of most variables to depend on marital status, and add the spouse variables $wage^*_{sit}$ and U_{sit}. We exclude the variables for men because the child variables are not statistically significant and the spouse variables have very small coefficients. Some of the variables are interacted with B_i and B_i^2 and/or with powers of t.

The composite error term e^h_{it} is determined by

$$e^h_{it} = \eta_i + \omega^h_{it} + \varepsilon^h_{it}\,; \quad \omega^h_{it} = \rho^h_{\omega^h}\omega^h_{i,t-1} + u^h_{it}.$$

It depends on the unobserved permanent hours component η_i, an autoregressive component ω^h_{it} with innovation u^h_{it}, and the i.i.d. error ε^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}. Together they capture serially correlated shifts and i.i.d. shifts in worker preferences, job-specific hours constraints, and length of unemployment spells. The hours measure $hours^*_{it}$ is equal to $hours_{it}$ plus the measurement error me^h_{it}.

We estimate the hours equation by 2SLS with the wage variables, marital status, the spouse variables, and children treated as endogenous. We estimate σ_η, $\rho^h_{\omega^h}$, and σ_{ε^h} by the method of moments. See Appendix B.4. Most of the variation in the wage conditional on education and potential experience is due to the permanent component μ_i and the autoregressive component ω_{it}, which is fairly persistent, so we interpret γ^h_w as a static uncompensated wage elasticity rather than an intertemporal substitution elasticity.

For men, the wage elasticity is near zero for the 1935 cohort, 0.089 (0.012) for the 1960 birth cohort, and increases to 0.13 for the 1974 birth cohort. It is close to the mean estimate reported in Bargain and Peichl's (2016) survey. Not surprisingly, annual hours worked have a strong negative link to U_{it}. Conditional on positive annual hours, and U_{it}, married men work 0.015 (0.008) more hours than unmarried men.

For women, the own wage elasticity is 0.244 (0.016). This value compares to a mean estimate of 0.43 for married women, 0.22 for single childless women, and 0.59 for single mothers reported by Bargain and Peichl (2016). The spouse wage elasticity is -0.193 (0.019), which is 0.07 above the average of Blau and Kahn's (2007) midpoint estimates for 1980, 1990 and 2000. Neither varies much across cohorts.[25] Married women increase hours in response to spouse's unemployment, consistent with many studies. 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 age 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.[26]

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_{it}^h and the shocks u_{it}^h to the autoregressive component ω_{it}^h are also substantial. Estimates are reported in Appendix Table B.4b.

3.2.4 Log Annual Earnings

Because the wage measure $WAGE_{it}^*$ is equal to annual earnings divided by hours (in levels, not logs),

$$earn_{it}^* = wage_{it}^* + hours_{it}^* \text{ if } earn_{it}^* > 0,\ hours_{it}^* > 0. \tag{6}$$

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 in cases where reported hours over the year are 0 ($P_{it} = 0$). (We do not topcode earnings.)

3.3 Nonlabor Income

Log nonlabor income depends on gender and marital status. For this reason we estimate gender-specific regression models for four transition statuses: single-to-single, married-to-married, single-to-married, and married-to-single. For those over age 25, the model is

[25] Blau and Kahn (2007) and Heim (2007) as well as Bargain and Peichl's (2016) meta analysis indicate that wage elasticities have declined across time. The papers do not discuss variation by birth cohort.

[26] 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.

$$nly_{it} = X_{it}^{nlgm}\gamma_X^{nlgm} + \omega_{it}^{nl} \tag{7}$$
$$\omega_{it}^{nl} = \rho_{gm}^{nl}\omega_{i,t-1}^{nl} + \varepsilon_{it}^{nlgm}, \tag{8}$$

where g denotes gender and m indicates whether the marriage transition status between $t-1$ and t is single-to-single, married-to-married, single-to-married, or married-to-single. Appendix Table B.1a displays the variables included as part of X_{it}^{nlgm} in the models. Variable ω_{it}^{nl} is an autoregressive term and ε_{it}^{nlgm} is an i.i.d. error. For married-to-married transitions, we use a common model for men and women because nonlabor income is not available separately for each spouse. All errors in the model are normally distributed with gm-specific variances.[27]

3.3.1 Family Earnings, Family income, and Family Income per Adult Equivalent

In the simulation model we define family income as the sum of a sample member's earnings, his or her spouse's earnings (if they are married), and nonlabor income:

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

Family income per adult equivalent is $Y\_AE_{it} = Y_{it}/AE_{it}$ where the adult equivalence scale is

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

We focus on the logs of the variables, y_{it} and y_ae_{it}, and also consider log family earnings $earn_{Fit}$, which excludes nonlabor income.[28]

3.4 Marriage Transitions

We use a straightforward modeling strategy that serves our purpose of analyzing the role of marriage in family income dynamics. We estimate the probability of entering a marriage conditional on the observed characteristics of the sample member. The divorce probability

[27] We estimate (7) by OLS for a given gender-marital-transition combination. We then use the residuals to estimate the ρ_{gm}^{nl} using OLS, along with the variance of ε_{it}^{nlgm}. Because nly_{it} is not available in odd years after 1996, we only use data through 1996 to estimate the ρ_{gm}^{nl}. We ignore measurement error. We separately use OLS to estimate (7) for single men at 25, single women at 25, and married individuals at age 25 and use the residuals to obtain estimates of the variance of ω_{it}^{nl} for each group at age 25. We use these equations to simulate initial values at age 25 of nly_{it} and ω_{it}^{nl}. The estimates of the models for nly_{it} are shown in Appendix Tables B.5a and B.5b.

[28] To simulate measured family income y_{it}^{*} for use in the analysis of model fit, we replace $earn_{it}$ and $earn_{sit}$ with simulated values of $earn_{it}^{*}$ and $earn_{sit}^{*}$.

is a function of the characteristics of both partners, marriage duration, and an unobserved marriage match component.[29] Keep in mind that "married" includes both legally married couples and couples who have been cohabiting for more than a year.

3.4.1 Single to Married

From age 25 forward, the transitions from single to married are determined by the probit model

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

The vector X_{it}^{SM} includes a constant and FEM_i. It also includes $EDUC_i$, $wage_{i,t-1}$, $P_{i,t-1}$ and $U_{i,t-1}$, a quadratic in age, and the interaction of all of these variables with FEM_i. In addition, it contains the index $CH\_VAR1_{i,t-1}$ measuring the presence of young children, a cubic time trend, $FEM_i \cdot B_i$, $FEM_i \cdot B_i \cdot EDUC_i$, B_i^2, and interactions of $CH\_VAR1_{i,t-1}$ with B_i and B_i^2. We report the probit coefficients in Appendix Table B.6.

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, but they do not matter for women. The results are consistent with evidence from many studies that, in the marriage market, labor market potential is more valued in men than in women. The effect of children on transitions into marriage has declined substantially across cohorts, which is consistent with the increase in single parent households in the US and other countries. Model simulations show the single-to-married probability is much higher for men than women after age 30, and the gap increases with age. This is one reason why the income effects of a divorce are more negative for women.

[29]The marriage transition and marital sorting parameters in our model implicitly depend on the supply of men and women of different types in the marriage market, the distribution of preferences over the characteristics of partners, and the value of being married relative to single life. They also depend on divorce laws, tax policy, labor market discrimination, and preferences for children. The parameters will change as these factors change. We use time trends and cohort terms to capture changes in these factors rather than explicitly modeling them. Our approach is fine for our purposes, which is to study the effects of shocks and education and permanent wage differences on the earnings and family income of an individual and to study the determinants of inequality, taking as given the marriage and labor markets that members of a cohort faced. But the model cannot be used to study the effect of a divorce law or a shift in the education distribution, because such changes would alter the equilibrium that the model parameters reflect.

3.4.2 Married to Married

For individuals who are married at $t-1$, the continuation of the marriage into period t is determined by the probit model

$$MAR_{it} = I[X_{it}^{MM}\gamma^{MM} + \varsigma_{j(i,t)} + \varepsilon_{it}^{MM} > 0],$$

where $I[.]$ is the indicator function, and the marriage shocks $\varepsilon_{it}^{MM} \sim N(0,1)$ are i.i.d. The model also includes the normally distributed marriage-specific heterogeneity term $\varsigma_{j(i,t)}$, where j indexes the marriage that i is in at year t. It captures the unobserved characteristics of the couple that improve marital stability. The vector X_{it}^{MM} includes a constant, FEM_i, $CH\_VAR1_{i,t-1}$, the absolute differences (relative to the mean arithmetic differences) between the education levels, ages, and wage rates of the spouses, and a cubic in t. It also includes an age cubic, education, $wage_{i,t-1}$, $P_{i,t-2}$, and $U_{i,t-2}$ for each spouse, all with gender-specific coefficients.[30] One would expect coefficients to differ by gender to the extent that economic roles in marriage differ by gender or if the effects of the variable on outside options differ by gender. The cohort variables include B_i^2, the interaction of B_i with the absolute difference in education levels, and gender-specific interactions of B_i with education and $P_{i,t-2}$. We include the square root, level, and square of marriage duration $MDUR_{i,t-1}$ as well as the interactions of these terms with B_i and with a quadratic in t. We show the estimates in Appendix Tale B.7.[31] Short of moving to joint estimation of the wage and marriage models, we were unable to find a way to allow the values of μ_i of the husband and wife to directly affect the marriage continuation probability. They enter indirectly through wage rates. We also ignored 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.

We find that $wage_{i,t-1}$ and $P_{i,t-2}$ both have a small positive effect on the stability of the marriage for men, but do not matter for women. The asymmetry is consistent with our findings for single-to-married transitions and with other papers. It indicates that the

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

[31] To improve the fit of the age profile of marriage-to-marriage transition probabilities for the late 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.7 (and the rest of the model). Then, we estimated a probit regression model of marriage-to-marriage transitions on a pooled data set of both the simulated data and the PSID data. The right-hand side of the probit model includes a cubic in age, a cubic in cohort, a quadratic in year and an interaction of these terms with a dummy indicating whether the observation is from the PSID (instead of a simulated observation). The estimated coefficients on the interactions with the PSID variables (and the PSID intercept) are used to form a regression index that we added to our model of marriage-to-marriage transition probabilities when simulating the model.

contribution of men to a marriage is based on earnings more than it is for women. We were mildly surprised to find that the effects of these variables did not change across cohorts.

Both husband and wife's education increase marital stability, consistent with other studies. 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 early and late 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, but we did not find a significant interaction with cohort. The estimate of σ_ξ is 0.505 (0.099). For comparison, a 4-year increase in the education of both spouses increases the probit index by 0.408 for couples born in 1960.

3.5 Spouse Characteristics at the Start of a Marriage

To be able to simulate the life of a sample member's spouse, we need to model all spouse characteristics that influence the path of the spouse's (and own) earnings, the couple's unearned income, and/or the marriage continuation probability—as well as the dependence of these characteristics on the sample member's own characteristics. We model this dependence (i.e. marital sorting) for five spouse characteristics: age, education, initial employment, permanent wage component (μ_{si}), and the autoregressive wage component (ω_{sit}) at the start of the marriage, as described below. There is no sorting on the hours components η_{si} and ω^h_{sit}.

Spouse's Education. For marriages in progress at age 25, the spouse's education is determined by a linear regression model with $EDUC_{si}$ as the dependent variable. The explanatory variables are $EDUC_i$, 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 replace $CH05_{it}$ with $CH05_{i,t-1}$, $CH612_{i,t-1}$, and $CH1318_{i,t-1}$, add B_i^2, and replace the interaction terms involving t with terms involving B_i. All equations are gender-specific. We estimate the equation by OLS. The mean squared error of the equations provides age- and gender-specific estimates of the variance of $\varepsilon_{it}^{ED_s}$, the random component of spouse's education. We assume $\varepsilon_{it}^{ED_s} \sim N(0, \sigma^2_{ED_s})$. The estimates are reported in Appendix Table B.8.

Spouse's Age. We estimate gender-specific linear regression models for a spouse's age at the start of the marriage. We do this separately for marriages in progress at age 25 and marriages that start after age 25. The determinants of spouse's age are $EDUC_i$, age polynomials, year polynomials, cohort polynomials, $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, and the interaction between B_i^2 and age. We assume the errors are normally distributed. Appendix Table B.9 presents the estimates.

Spouse's Labor Market Status. To determine a spouse's initial employment status

(N, E, or U), we estimate multinomial probit models of employment status separately by gender and by whether the marriage is ongoing at age 25 or is one that begins afterwards. Spouse's employment status depends on $EDUC_i$, the wage, PE_{it}, PE_{it}^2 and PE_{it}^3 (females only), $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, employment status, and a quadratic in calendar time. The model estimates for spouses after age 25 are in Tables B.10 (for female spouses) and B.11 (for male spouses). Spouses do not sort directly on the employment heterogeneity term ν_i.

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

We assume that the distribution of μ_{si} depends on μ_i and that the distribution of ω_{sit} at the start of the marriage depends on the lag of ω_{it}. Let the subscripts f or m indicate the gender of the individual or the spouse. We continue to use s to indicate that a variable or parameter refers to the spouse. The model for μ_{sfi} of the female spouse is

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

The value of ω_{sfit_0} for a marriage that starts in t_0 is related to ω_{mit,t_0-1} according to

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

We restrict the coefficient linking μ_{sfi} and μ_{mi} to equal the coefficient linking ω_{sfit_0} and ω_{mi,t_0-1} (that is, $\gamma_{m\mu}^{\mu_s} = \gamma_{m\omega}^{\omega_s}$) because the coefficient for ω_{sfit_0} and ω_{mi,t_0-1} is poorly identified. We also impose the natural restriction that the variances for female (male) spouses equal the variances for female (male) sample members (i.e., $Var\left(\mu_{sfi}\right) = Var\left(\mu_{fi}\right)$ and $Var(\omega_{sfit_0}) = Var(\omega_{fit_0})$). After a marriage starts, ω_{sfit} evolves according to (3) 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 the wage components of male spouses takes the same form.

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.5). All parameters depend on whether $B_i \leq$1962. The estimates are shown in Appendix Table B.14. For female sample members, the estimates of $\gamma_{f\mu}^{\mu_s}$ are 0.394 (0.008) and 0.387 (0.014) for those born before 1962 and those born after, respectively. For male sample members, the corresponding values are 0.312 (0.007) and 0.288 (0.009). Thus, there is strong sorting on the wage components, the effects are larger for women than for men, and there is little change across cohorts.

3.6 Fertility after Age 25

Births after age 25 are determined by gender- and marital status-specific probit models. Each of these models is of the form

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

The probit estimates are in Appendix Table B.15. For unmarried individuals, the explanatory variables are $CH05_{i,t-1}$, $CH612_{i,t-1}$, $CH1318_{i,t-1}$, a cubic in age, a quadratic in year, B_i^2, $EDUC_i$, and the interaction between $EDUC_i$ and a quadratic in B_i. For both single men and single women, education has a negative effect. We exclude the wage rate from the models for single men and women because it is statistically insignificant, regardless of whether we include cohort interactions. For married individuals we start with the variables for singles and then add a quadratic in spouse's age, year cubed, $wage_{i,t-1}$, $wage_{si,t-1}$ and $EDUC_{si}$. Both own wage and spouse's wage enter with small positive coefficients. Spouse's education also enters positively. A shortcoming of the model is that fertility is not determined jointly with labor supply.

3.7 Some Limitations of the Model and Estimation Strategy

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

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.12.

Overall, our model fits the data reasonably well, though the fit is not 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 early cohort. A possible explanation is that the PSID has relatively few observations for this cohort early in the lifecycle. The rest of this section summarizes the fit for specific groups of variables.

Labor Force Status. Overall, our model fits the mean 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 early cohort before age 35. As a result, we slightly and consistently underpredict employment for the same group.

Wages and Hours. For log wages and log hours, the model fits the means and standard deviations as well as the age profiles for both men and women quite well overall. For the early cohort, the model understates the log wage for women at young ages. For the late cohort, the model slightly overpredicts the wage for women at ages 35-45, though it fits the overall age profile reasonably well.

Earnings. The model fits the age profile of log earnings for men quite well overall. For women, the model overpredicts earnings somewhat for all cohorts. As a result of the overprediction, the overall mean of log earnings for women in the early cohort is 9.09 in the simulated data but 8.97 in the PSID (the miss is 0.12 log points). For the other two cohorts, the miss in the overall mean of log earnings for women is 0.17 log points.[32]

Marriage. On the whole, the model fits the overall marriage rates and age profiles fairly well for both men and women. For the early cohort, the model somewhat underpredicts marriage rates at young ages for both men and women, but it does better at older ages. As a result of the miss at young ages, the overall marriage rate for men in this cohort is 0.86 in the model and 0.88 in the data, and the corresponding means for women are 0.80 and 0.83. For the late cohort, the model overpredicts marriage somewhat for women at older ages, but it fits the overall marriage rate for women fairly well (0.71 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 early cohort, the model slightly underpredicts log family income (y) for women and overpredicts y_ae for men, especially at younger ages. For women in this cohort, the overall mean of log family income is 11.0 in the simulated data and 11.03 in the PSID (the fit for this group is very good for y_ae). For men in this cohort group, the overall mean of y is 11.08 in the simulated data and 11.07 in the PSID.

Spouse Variables. The model fits the means and standard deviations of spouses' age and education quite well, for all cohorts. 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 earlier cohorts, but less so for the more recent cohorts. For the late cohort, the estimated coefficient is somewhat understated in the simulated data for men (0.21 versus 0.33 in the PSID data).

Dynamic Fit of the Model. We evaluate the dynamic fit of the model by estimating 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 $k = 1, 3, 6, 8$ (we do this separately for men and women). For all cohorts, the model somewhat understates the

[32]Part of the miss between simulated and PSID earnings is the result of their different definitions. Simulated log earnings equals the log wage plus log hours. But as explained in Section 2, the log of our PSID earnings measure is sometimes less than the sum of our PSID log wage and log hours measures; this is why simulated earnings can overpredict PSID earnings even when there is no overprediction for hours or wages. Note, however, that although we use the PSID earnings measure to assess model fit, this measure does not play a direct role in estimation of the model, in the model simulations, or in the variance decompositions.

persistence in earnings for both men and women. For example, for the baby boom cohort, the model understates the regression coefficient for men by about 0.09 at the first lag and 0.14 at the 8th lag, and for women by about 0.12 at the first lag and the 8th lag. The miss in earnings persistence is primarily driven by an underpredicted persistence in hours. 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.

Event Studies of Marital Transitions. We also compare the average paths in the PSID of work hours, earnings, and family income in the years around a change in marital status to the corresponding average paths in the simulated data. We do so controlling for event fixed effects. Overall, the difference in the averages of the response over the first few years before and after the marriage begins correspond reasonably well, except for marriage for men. For women, both in the case of earnings and hours we overstate how immediate the impact of marriage is. This is not surprising, because the model does not include a distributive lag or partial adjustment mechanism for hours and for fertility. The pattern is similar, but in the opposite direction, for divorce. For both men and women we overstate the immediate impact of divorce, though only slightly so for women. For family income, the marriage and divorce event studies in the simulated and PSID data match fairly closely for both men and women, though for men especially we see an overstatement of the impacts of both divorce and marriage. This is especially true for family income per adult equivalent. For women, family income and family income per adult equivalent match pretty well. If anything, we may be understating the differences between men and women in the effects of a divorce on the path of y_ae_{it}.

While we present impulse responses at annual frequencies below, we have more confidence in the average response over the first few years rather than the immediate response.

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

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

5.1 Approach to Estimating Impulse Response Functions

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 through age 55. 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).[33] For example, we impose that all married individuals in the gender-birth cohort group become unemployed, or all singles who had not previously been married 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 then compare the mean path of a given outcome variable (e.g. log earnings) in 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 divorce shock, we compare the means for the counterfactual and baseline simulated lives for those individuals who were in their first marriage at age 33. The IRFs report the deviation of the counterfactual mean path of the outcome variable from its baseline mean path.

A word about the figures in this section. In general, point estimate lines display the gender-cohort group'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 band lines are thinner but of the same color and line pattern. Confidence interval estimates are based on 500 bootstrap replications of the model and IRF estimation procedure.

5.2 The Effects of Divorce and Marriage

Figure 1 shows the mean response of the log wage, log hours, and log earnings to an exogenous divorce shock imposed on married individuals at age 34. We only consider individuals who are in their first marriage, but the results are not sensitive to this choice. Panel A is for married women in the early birth cohort. Following a divorce, log earnings ($earn_{it}$) (solid blue line) for women in this cohort rise by 0.75 log points and remain elevated (relative to the baseline mean) for many years. The increase reflects a sharp increase in $hours_{it}$ (short-dashed orange line) and a smaller, more gradual increase in $wage_{it}$ (long-dashed green line) peaking at 0.08 three years after the divorce. It also reflects an additional effect of divorce on the probability of working nonzero 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 $earn_{it}$.) 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.

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

Panel B presents corresponding results for the baby boom (1945–62) cohort. It shows a striking change across cohorts. The positive effect of divorce on $earn_{it}$ peaks at 0.33, which is less than one-half of the value for the early cohort. The smaller value reflects much smaller increases in $hours_{it}$ and in $wage_{it}$, as well as a much smaller increase in P_{it} (not shown). 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, and at higher wage rates than those in the prior cohort. For the early cohort, the means of simulated $earn_{it}$, $hours_{it}$, $wage_{it}$, and P_{it} for married women at age 33 are 8.17, 5.96, 2.43, and 0.45. These values rose to 9.21, 6.66, 2.67, 0.77, respectively, for the baby boom cohort. In contrast, the values for married men at age 33 change very little, and the values for single women start at a much higher level and increase by a much smaller amount (0.11 in the case of $earn_{it}$, not shown).

Panel C presents the divorce IRFs for women in the late (1964-74) cohort. The effect of divorce on $earn_{it}$, $hours_{it}$, and $wage_{it}$ declines compared to the middle cohort. The increase in $earn_{it}$ peaks at 0.24 and eventually becomes slightly negative, although the estimates after age 50 should be viewed with caution because they are outside the sample for most members of the cohort.

The estimates of the effects of divorce for men are shown in Figure 1 panels D, E, and F. In contrast to the large increases for women, men in the early cohort experience a drop in earnings by 0.09 after a divorce and by about 0.06 after 10 years (relative to baseline). But for men, the earnings decline *increases* in magnitude across cohorts. For the late cohort, the earnings decline is 0.15 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 ($earn_{Fit}$, long-dashed lines) and log family income per adult equivalent (y_ae_{it}, short-dashed lines). There are three main findings. First, divorce has much more negative effects on $earn_{Fit}$ and y_ae_{it} for women than for men in every cohort. Women in the early cohort experience a drop in $earn_{Fit}$ equal to -2.0 (or 86%) with a gradual recovery to -0.35 (30%) at age 55 (relative to baseline). The corresponding values for men are -0.29 and -0.10. The much larger drop for women reflects the fact that earnings of married men account for 84% of family earnings on average between the ages of 30 and 33 for the early cohort.

The gender asymmetry in the loss of $earn_{Fit}$ is reflected in the IRFs for y_ae_{it} (short-dashed lines). Women in the early cohort experience a large drop in y_ae_{it} equal to -0.75 followed by a partial recovery to -0.13 at age 55. In contrast, men in this 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 $earn_{Fit}$ is -2.0 (86%) for the early cohort, -1.55 (79%) for the baby boom cohort and -1.50 (78%) for the late cohort. In contrast, for men the corresponding declines are -0.29 (25%), -0.49 (39%), and -0.63 (47%). Underlying this shift is a gain in the (female) spouse's share of family earnings for men married between age 30 and 33 from 84% in the early cohort to 59% in the late cohort.

Third, for women the effect of divorce on y_ae_{it} declined in magnitude from -0.75 for the early cohort to –0.69 for the late cohort. In contrast, for men the effect of divorce fell from a 0.05 boost to a -0.16 drop. Thus the gender differential has declined substantially, although it remains large.[34][35]

We wish to stress that the specific year-to-year timing of the responses should be viewed with caution. As previously noted, the dynamic specification of the model is simplified in a number of dimensions. In particular, we do not include distributed lags in the impact of divorce on the labor market variables. But it is clear that divorce has a large negative and persistent effect on y_ae_{it} for women, and a growing, negative effect for men.

Appendix Figure D.1a displays the cohort-specific dynamic response of $wage_{it}$, $hours_{it}$, and $earn_{it}$ to an exogenous "marriage" shock imposed on all women and men who are single at age 33. Roughly speaking, the estimates of the effects of entering marriage are equal and opposite in sign to the effects of divorce. For women, wage rates, hours, and earnings all fall, but the magnitude of these effects declines dramatically across cohorts. Appendix Figure D.1b shows that the positive effect on y_ae_{it} for women is more similar across cohorts. 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.[36]

[34]IRFs for the response of nonlabor income to a divorce show an increase for women after a divorce (not reported). It constitutes a small share of family income for most individuals.

[35]We also simulated the effects of a divorce at ages 29, 33, 40, and 45. The general pattern for women is that the earlier the divorce, the more positive the response of log hours, log earnings, and to a lesser extent, the wage, in the first few years after the divorce. For example, in the case of the baby boom cohort, earnings rise by about 0.44, 0.32, 0.23, and 0.20 following a divorce at age 29, 33, 40, and 45, respectively. The differences are small fifteen years after the divorce. For y_ae_{it}, the earlier the divorce, the more negative the effects for the early cohort. The opposite is true for the baby boom and the late cohorts, but the differences are not large. For men, the effect of a divorce on y_ae_{it} and on $earn_{Fit}$ becomes more negative with the age at which the shock occurs but the differences are not large. Our conclusions about gender differences are not affected.

[36]Appendix Figure D.8 reports the dynamic response of earnings and y_ae_{it} to a birth to single and married women. The negative effect on earnings declines somewhat across cohorts. See discussion in Appendix D.2.

5.3 Unemployment Shocks

Figure 3 displays the response of earnings and income for married individuals who worked positive hours at age 33 to an unemployment shock at age 34.[37] Keep in mind that an unemployment shock means that the person works positive hours but has some unemployment over the year. The solid blue line is the IRF for $earn_{it}$. For women in the early cohort (Panel A), $earn_{it}$ declines by -0.08, rebounds fairly quickly as hours recover, and returns to the baseline value in about 8 years.[38] The negative effects of the unemployment shock grow larger across cohorts for women. For the late cohort, $earn_{it}$ falls by -0.26. The growth in the earnings response is mirrored in an increase of the responses of $earn_{Fit}$ (short-dashed line) and y_ae_{it} (long-dashed line).

The corresponding IRFs for married men from the early cohort (Panel D) show a drop in $earn_{it}$ of -0.25 followed by a recovery to -0.05 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 $earn_{Fit}$ and y_ae_{it}. For married men in the late cohort, the initial drop in $earn_{it}$ after an unemployment shock is even larger: -0.44. 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 early cohort to -0.28 for the late cohort even though the negative effect of unemployment on $earn_{it}$ increases by nearly 0.20 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 wives' earnings.

Appendix Figure D.3 shows the effects of an unemployment shock for single women and single men. For the early cohort, the effect on earnings is -0.15 for single women and -0.24 for single men. The effects on y_ae_{it} are -0.12 and -0.20. The effects are substantially more negative for both single women and single men in the late cohort. For example, for single men the effects are -0.41 for earnings and -0.34 for y_ae_{it}. Both single men and single women experience a larger percentage decline in y_ae_{it} in response to a shock than married individuals because they do not have the earnings of a spouse.

[37]Note that we only shock those who had positive hours but were experiencing no unemployment ($E_{it} = 1$) at age 33 in the baseline simulation. Estimates are very similar for shocks at age 29, 40, and 45, except that the short-run effect on earnings for married women in the early cohort is about half as large for the age 29 shock (not shown).

[38]We computed IRFs of the response of $wage_{it}$, $hours_{it}$, and E_{it} to an unemployment shock for the 12 gender, marital status, and cohort combinations (not reported). In all cases, the initial drop in earnings is entirely due to hours. The decline in $wage_{it}$ is smaller but more persistent.

5.4 Wage Shocks

Figure 4 reports the IRFs corresponding to a positive, one-standard-deviation innovation in the persistent wage component ω_{it} for married men and women at age 34. The shock is 0.186 for both married and unmarried women and 0.184 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 effect on y_ae_{it}. The size of the earnings effect grows across cohorts, but the relative size of the effect on y_ae_{it} grows considerably 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 peak effect on earnings grows across cohorts from 0.18 to 0.21. The peak effect on y_ae_{it} is 0.14 for the early 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, peaking at 0.11 for the late cohort, once again reflecting the shifting relative contributions of male and female spouses across cohorts. The estimates for unmarried women and men are more similar, and do not change much across cohorts (not shown). For unmarried women, the impact of the shocks on y_ae_{it} is closer to its impact on earnings.

The size of the shock is smaller and the effects are more persistent when we use estimates of the wage model with ρ^w_{it} constrained to 0.9, but the differences across gender and across cohort are very similar (Appendix Figure D.5).

6 Effects of Education and Permanent Wage Differences

Next we examine generational change in the effects of education differences and of permanent wage heterogeneity on earnings and family income over the lifecycle. To examine the effects of education differences, we use our model to first simulate a large number of individuals, starting at age 25 through age 55, 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 report, at each age, the difference in the mean of log earnings (as well as of y_ae_{it}) 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 mean of the distribution of the permanent wage component μ_i to its base case value of zero and the second simulation sets the mean of μ_i to one standard deviation above zero. We then report the difference in the means of log earnings (and of y_ae_{it}) at each age across the two simulations.[39]

6.1 Education Differences

Figure 5 panels A, B, and C present the difference between the mean paths of earnings (solid line) and of y_ae_{it} (dashed line) for women with 16 years of education and women with only 12 years of education. The results in panel A are for the early cohort. The education gap in earnings rises from about 0.84 at age 30 to 0.93 at age 55. Appendix Figure D.7 shows that education differentials in both hours and the wage rate contribute to the gap. The gap in hours is U-shaped reflecting the fact that more educated women have children later in life. The use of log earnings (even with a floor of log(1300)) amplifies differences at the low end of the earnings distribution, and it amplifies the importance of the strong link between education and the probability of working positive hours.

The education differential in y_ae_{it} (dashed line in Figure 5 Panel A) is also large and varies within a narrow band around 0.5 throughout the lifecycle.

The middle cohort (Panel B) shows a similar but starker pattern as women in the early cohort. The picture that emerges is one in which at very young ages there is a large log earnings gap as more-educated women are less likely to be married and, therefore, more likely to participate in the labor market. The gap falls 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 falls as women reach their late 30s and early 40s before rising (to close to its original level).

For the late cohort (Panel C), the lifecycle patterns in the education gaps in earnings are more muted, especially early in adult life, when women with 16 years of education consistently earn about 0.75 log points more than women with 12 years of education. The profile of the gap in y_ae_{it} is similar to the pattern for the baby boom cohort, but slightly larger. This is especially true after age 45, though it is worth stressing that for the late cohort the simulations after age 50 are outside the support of the data for those born after 1968.

Figure 5 panels D, E, and F report results for men. The education differential in earnings (solid line) rises dramatically with age for all cohorts. For the early cohort the gap rises from 0.22 at age 26 to 0.82 at age 55. The baby boom and the late cohorts see a somewhat higher

[39]Repeating this exercise with the wage model obtained with ρ^{ω}_{it} restricted to 0.9 yields very similar results, except that to a fairly close approximation, the age-specific effects are reduced by the ratio of the estimates of σ_μ with and without the restriction. The ratio is 0.810 for men and 0.745 for women.

earnings gap at every age. For the late cohort, the gap is 0.23 at age 26 and peaks at 0.98 at age 52. Almost all of the increase across cohorts is due to a substantial widening of the gap in hours across cohorts prior to age 50 (Appendix Figure D.7). For men the education gap in y_ae_{it} at age 26 is about 0.38 for all three cohorts. The values at age 50 for the early, middle, and late cohorts are 0.49, 0.49, and 0.59, respectively.

6.1.1 The Contribution of Marriage and Sorting Channels to Education Differences in Family Income

Next we examine the extent to which the education differential in y_ae_{it} that we just showed is due to an effect of education on marital status transition probabilities (the marriage channel) versus an effect on whom one marries (the sorting channel).

To do so, we use simulated data from the baseline model to estimate versions of the marriage transition equations and sorting equations that depend only on the vector $X_{B_i,a_{it},t}$, which consists of a constant, B_i^2, and third- or fourth-order polynomials in age and in calendar time. For example, the equation for transitions from single to married is replaced with gender-specific versions of the equation

$$\text{Mar}_{it}=1[\ X_{B_i,a_{it},t}\gamma^{SM}+u_{it}^{SM}];\ \text{Mar}_{i,t-1}=0 \tag{9}$$

where u_{it}^{SM} is an i.i.d. standard normal error. The equation for marriage-to-marriage transitions takes the same form as (9) but with the composite error term $\varsigma_{j(i,t)}+u_{it}^{MM}$. To give another example, the no-sorting model for spouse's education is a linear regression of $EDUC_{si}$ on $X_{B_i,a_{it},t}$. Replacing the marriage transition equations and/or the marital sorting equations with the functions of age, birth cohort, and time amounts to shutting down the marriage and/or sorting channels through which personal characteristics and shocks affect outcomes.[40]

We construct the impact of education differences in the same manner as we did previously, but using the alternative versions of marriage and sorting equations to define both the base case and the counterfactual. We present three additional counterfactuals. In the first, only the marriage channel is shut down. In the second, only the sorting channel is shut down. In the third, both the marriage channel and the sorting channel are shut down. The gap between these differences and the differences based on the actual model is the estimate of

[40] When we shut down the marriage channel, we draw labor market status, marital status, marital duration, and number of children at age 25 using sample estimates of the probability of each combination of labor market status, marital status, marital duration, and number of children at age 25 conditional on only gender and cohort, rather than on education, gender, and cohort.

the contribution of the marriage and/or sorting channel to the overall difference.[41]

In the panels of Figure 6, the solid line is the education differential in y_ae_{it} (i.e. the same as the dashed line in Figure 5). The long-dashed lines in Figure 6 are the differential in the counterfactual case of no sorting; the short-dashed lines are the no marriage channel case; and the dot-dashed lines are for the counterfactual with no sorting and no marriage channels. Panel A shows that for women in the early cohort, eliminating the marriage channel has almost no effect on the female college-to-high school differential in the path of y_ae_{it} (see the distance between the solid and short-dashed lines). Eliminating both the sorting and the marriage channels reduces the education differential by an amount that increases from about 0.15 log points at age 30 to about 0.18 in the early 50s (the difference between the solid line and the dot-dashed line). Almost all of the effect is from sorting. The 0.16-0.18 reduction is very large relative to the base of about 0.5.

Turning to the late cohort in panel C, one can see that the contribution of sorting (the difference between the solid and long-dashed lines) varies considerably over the lifecycle. It contributes about 0.10 of the education differential at age 30, 0.14 at age 40, and an average of about 0.16 after age 50. Thus positive assortative mating plays a critical role in the economic return to education for women, but it is somewhat less important for more recent cohorts of women, who marry less and work more. The contribution of the marriage channel (solid line minus short-dashed line) grows in importance across cohorts from essentially zero for the early cohort to an average (across age) of about 0.05 for the late cohort.

For men in the early cohort (Panel D), eliminating the sorting channel reduces the college-to-high school differential in y_ae_{it} by less than 0.03 until about age 43 and then the sorting effect rises gradually to about 0.08 at age 50. Thus assortative mating by education matters much more for women, largely because married women contribute a smaller share of family income. However, the contribution of sorting grows across cohorts for men, and the gender gap in the importance of assortative mating is smaller in the late cohort. The marriage channel effect also grows across cohorts and with age, contributing 0.08 at age 50 for the late cohort.

6.2 Permanent Wage Differences

Figure 7 reports the effect of a one-standard-deviation increase in the mean, $\bar{\mu}$, of μ_i from its base case value of zero on the average paths of $earn_{it}$ and y_ae_{it}. The standard deviations of μ are 0.33 for women and 0.35 for men. Panel A is for women from the early cohort. The solid line shows that the mean of $earn_{it}$ for high-$\bar{\mu}$ women starts at 0.24 above the value for

[41] An analogous approach can be used to measure the influence of the marriage channel and sorting on responses to shocks. See Appendix D.1 and Appendix Table D.2 for the divorce shock case.

mean-zero μ women at age 30. This gap gradually grows to 0.41 at age 50. Hours differences account for about one-fourth of the earnings gap (not shown). The permanent wage gap in earnings averages about 0.41 for the baby boom cohort and 0.44 for the late cohort, likely reflecting an interaction between higher wage potential and higher labor force participation in the more recent cohorts. The dashed 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 0.21 for women in the early cohort to 0.27 for women in the late cohort.

The patterns for men in Figure 7 panel D show that high-$\bar{\mu}$ men earn about 0.38 more than zero-$\bar{\mu}$ men on average over the lifecycle in the early cohort, a gap that is well above the corresponding gap for women. The size of the effect increases across cohorts, as was the case for women. The effect of μ on the path of y_ae_{it} (dashed line) increases only slightly across cohorts (averaging across all 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.

Appendix Figure D.6, Panel A shows that for women in the early cohort, eliminating both the sorting and marriage channels lowers the gain in y_ae_{it} from a one-standard-deviation increase in the μ_i distribution from an average across ages of about 0.21 to about 0.15 (the difference between the solid and dot-dashed lines). 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 both the marriage and the sorting channels reduces the effect of the shift in μ on y_ae_{it} by about 0.01 early in life and about 0.03 at age 45 for the early cohort (Panel D, difference between solid and dot-dashed lines). 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 the μ increase.[42] For men the contribution of sorting to the effect of μ on y_ae_{it} increases from a lifetime average of 0.02 for the early cohort to 0.08 for the late cohort, narrowing the gender gap in the importance of sorting.

7 Variance Decompositions of Lifetime Earnings and Family Income

In this section we use our model to decompose, separately for each gender-cohort group, the variance (across individuals in that group) of lifetime family income per adult equivalent (and lifetime earnings) into the contributions of several sources of variation. The sources

[42]For men, the marriage channel does make a significant contribution after age 40 for the late cohort.

are: (1) education; (2) the permanent wage component μ_i; (3) the permanent employment component ν_i; (4) the permanent hours component η_i; (5) the i.i.d. shocks to employment status plus variation in initial employment conditional on education, marital status, and number of children; (6) 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}; (7) 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}; (8) the initial draw and shocks to the autoregressive component of unearned income; (9) the random component $\varepsilon^{ED_s}_{it}$ of the spouse's education; (10) the random component $\tilde{\mu}^{s}_{i}$ of μ_{si}; (11) η_{si} and ν_{si}; (12) 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 (13) the contribution of random variation in marriage histories conditional on the vector $[\mu_i, \eta_i, \nu_i, \omega_{it(a_{i25})}, EDUC_i]$.[43]

7.1 Variance Decomposition Methods

We perform the variance decompositions as follows. For each gender-cohort group, we first use our model to simulate 100 lives for (each of) a large number of individuals from age 25 to age 55. For each simulated life, we compute the annual average, from age 25 to 55, of y_ae_{it}, which we call y_ae_i. We then compute the variance (across person-lives in that gender-cohort group) of those lifetime averages y_ae_i.[44] 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 for each simulated life), and we use the difference in the variance of the lifetime averages, relative to the variance in 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.[45]

Our calculations take as given the other parameters of the model, which is the approach taken by Altonji et al. (2013) in their study of male earnings. In reality, the parameters of the model reflect equilibrium behavior in the economy given shocks, the distribution of education, the distribution of the permanent wage, the extent of social insurance, and so on. The parameters would be different in a world in which wage shocks, the variance of education, or the other sources of variation we consider are zero. Our variance decompositions measure the relative contribution to inequality of the factors we consider holding the model parameters

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

[44] Here we focus on the lifetime average of y_ae_{it} (as well as lifetime average of $earn_{it}$), which are averages of logs. Decompositions of the variance of the log of the lifetime average of the income *level* Y_{it}/AE_{it} are similar (not reported).

[45] 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.

fixed.

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 the marriage duration variable at age 25 ($MDUR_{i25}$) and the vector of values (0s or 1s) that the marriage indicator 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 effects for each unique value of $MHIST_i$. In practice, we use regressions of lifetime income where 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 because these variables are hard to summarize in a simple way, wage and labor force shocks have only a moderate influence on marriage transitions, and hours shocks have no effect.

Note that the variance contributions in our decompositions do not sum to 100%, for three reasons. First, because the model is nonlinear, interactions among the factors can amplify the contribution of some factors and lead the marginal contribution of other factors to be negative.[46] This turns out to be particularly important for labor force status shocks. 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}, the marriage match quality term $\varsigma_{j(i,t)}$, or the i.i.d. spousal employment shocks. Third, we do not consider the effect of random variation in the number of children, which we suspect is quantitatively significant. For example, an unplanned pregnancy influences the path of marital status and has mechanical effects on AE_{it}. However, the effects of the various factors we do consider that operate through number of children are accounted for.[47]

[46]Many of the equations of the model involve nonlinear mappings from the error components and other variables to the outcomes. Furthermore, marital status, children, labor force status, and other variables interact in the model. Finally, y_ae_{it} is the log of the sum of the levels of own earnings, spouse's earnings, and unearned income divided by AE, where the latter in turn depends on marital status and the number of children.

[47]Column 16 in Appendix Tables E.1-E.3 reports the sum of percentages explained by the factors we consider. The difference between this value and 100 captures the combined contributions of the factors that we omit and the nonlinear interactions.

7.2 Variance Decomposition Estimates

The variance decompositions of y_ae_i by gender and cohort group are presented in Figures 8a and 8b. Figure 8a displays the contributions of the sample members' own characteristics (e.g. EDUC_i and μ_i) and shocks, while Figure 8b 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 earlier cohort groups. The height of the colored bars denotes the percent of the variance in $var(y\_ae_i)$ 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.[48]

Starting with Figure 8a, the first set of bars shows the contribution of variation in education to $var(y\_ae_i)$. Education plays a very important role for both men and women and for all cohort groups, but its importance has declined. For women the contribution fell from 35.3% of the variance for the early cohort to 24.8% for the later cohort. For men the contribution of education fell from 38% to 29.9%. 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). A comparison to the variance decomposition of $var(earn_i)$ (see Appendix Tables E.1-E.3, row 1) reveals that the relative importance of education for own earning versus family income is smaller for women, reflecting differences in the importance of spouse's earnings.

The second set of bars in Figure 8a shows that the permanent wage component μ_i is also very important, contributing between 13.8% and 29.7% of $var(y\_ae_i)$. It plays a larger role for men than for women. However, the difference between men and women has narrowed over time. As the figure shows, the importance of μ_i for women has increased from 13.8% for women in the early cohort to 21.6% for those in the late cohort. The increase in the contribution of μ_i is also seen in the decomposition of $var(earn_i)$ and 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,

[48]Note that the variance of y_ae_i differs across gender and cohort groups, so a given percentage contribution to the variance translates into a different contribution to the level of $var(y\_ae_i)$. Appendix Tables E.1-E.3 show (column 15, bottom row) that the standard deviation of y_ae_i increased from 0.62 for women in the early cohort to 0.66 for women in the late cohort, and from 0.60 for men in the early cohort to 0.66 for men in the late cohort. 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.

the importance of μ_i for men rises from 26.4% to 29.7% between the early and baby boom cohorts, but then falls back to 26.4% for the late cohort. The pattern is also reflected in a drop for men in the contribution of μ_i to $var(earn_i)$ that is probably due to a 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 markedly, from 12.6 percentage points for the early cohort to just 4.8 percentage points for the late cohort.

The next two sets of bars show the contributions of the permanent components in employment and hours, ν_i and η_i. The contribution of the permanent employment component ν_i rises from 4.5% in the early cohort to 9.8% in the late cohort for women. For men, the contribution of ν_i has risen from 3.4% to 17.5%. The increase for women is due to a large increase across cohorts in the average wage rate and in average hours conditional on participation more consequential. It also reflects the larger female share of family earnings for more recent generations. For men, the increase likely stems from a completely different force: the drop in male labor force participation.[49] As men as a group became less permanently attached to the labor force, variation in ν_i began to play a much larger role in determining nonparticipation. Interestingly, the contribution to the variance of family earnings is even larger than for y_ae_i (Appendix Tables E.1-E.3). This suggests that the effect of ν_i on nonlabor income (through, say, transfers) partially offsets its effect on earnings, reducing its overall contribution to $var(y\_ae_i)$. The contribution of the permanent hours component η_i for women rises from 1.8% for the early cohort to 3.3% for the late cohort. For men, the contribution rises from 1.4% to 3%. This component accounts for roughly 3% of $var(earn_i)$ on average for both genders.[50]

The two sets of bars that follow in Figure 8a show the contributions of the transitory shocks to the wage and to hours conditional on employment status. They are much smaller than the contributions of the permanent components μ_i and ν_i in large part because these components are transitory in nature, and their effect consequently fades over the course of a lifetime.[51] However, when we perform the variance decompositions using the estimates of the wage model with the autoregressive coefficient ρ^w_{it} restricted to 0.9, the contribution

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

[50] Following the discussion in section 3.2.2 we checked sensitivity of the decompositions to using estimates of the labor force status model with σ^2_ν restricted to 1.5 times the unrestricted estimate (not reported). The resulting estimates of the variance contribution of ν_i for women are 3.9%, 8.6%, and 13.4% for the early, baby boom and late cohorts, respectively. The values for men are 3%, 6.9%, and 16.6%. Averaging across cohorts, the estimates rise by a factor of 1.08 for women and 1.37 for men. The contributions of the other components do not change much.

[51] 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.2b.

of the wage shocks to $var(y\_ae_i)$ more than doubles (Appendix Figure E.1). For women, the contribution rises to 3.9% for the early cohort and to 6.1% for the late cohort. For men, the contributions average 10.3% across cohorts. The increase in the importance of the wage shocks is accompanied by an offsetting reduction in the estimated contribution of the permanent wage component μ_i. The finding that the importance of the combined contribution of μ_i and the wage shocks grew for women relative to men is not sensitive to the choice of ρ^w_{it}. The increased importance for women is consistent with women's increased participation in the labor market and the larger share of women's earnings in overall family income.

The final set of bars in Figure 8a displays the contribution of employment shocks. We shut down employment shocks by setting E_{it}, U_{it}, and N_{it} to their predicted probabilities conditional on the variables in the labor force status model, including ν_i, but with the shocks set to 0. We find substantial negative effects, especially for women. The reason for the negative contribution is as follows. When we "turn off" employment shocks, we set participation and unemployment to their mean probabilities for each person-period. For both men and women in all three cohorts, the predicted probabilities are positively correlated with the wage rate and earnings conditional on $P_{it} = 1$ at all leads and lags (except contemporaneously). Consequently, labor market status shocks have the effect of reducing the influence of persistent sources of variation in wage rates on the variance of lifetime earnings. In most cases, this effect is sufficient to offset the positive variance contribution of labor market shocks on the income and family income variance at a given age.

Turning to Figure 8b, 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 3.3%, 5.4%, and 7.9% for the early, baby boom, and late cohorts, respectively. For men, the contribution has fallen somewhat, from 3.4% for the early cohort to 2.7% for the late cohort. Overall, variation in marital histories matters a little more for women than for men. Not surprisingly, marital history is much more important for (unadjusted) family income, accounting for 28% and 16.8% of $var(y\_ae_i)$ for women and for men in the late cohort, respectively (Appendix Tables E.3).

The remaining sets of bars in Figure 8b show the contributions of (1) the random component $\varepsilon^{ED_s}_{it}$ of the spouse's education; (2) the random component $\tilde{\mu}^s_i$ of μ_{si}; (3) spouse's wage shocks including 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 (4) the spouse's hours and employment heterogeneity terms η_{si} and ν_{si}. We highlight two main findings. First, the contributions of spouse characteristics are much larger for women than for men. Second, these contributions have declined over time for women and increased for men. For example, the contribution of random variation in spouses' education edged down from 5.8% to 5.5% for women across cohorts and increased from essentially zero to 2.4% for men. The contribution of $\tilde{\mu}_i^s$ dropped from 12.2% to 7.2% for women and increased from 0.4% to 4.0% 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 in the sources of lifetime inequality.

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 $var(y\_ae_i)$ 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 $var(y\_ae_i)$ with sorting (our base case simulation) and $var(y\_ae_i)$ under random matching, divided by the variance under random matching. We find that sorting is much more important for women than for men in the early cohort, but gender differences are small in the late cohort.

The results are shown in columns (1)-(4) of Appendix Table E.4. For women (Panel B), marital sorting increases $var(y\_ae_i)$ by 16.8% on average across cohorts (Panel B, 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 16.1% for the early cohort to 7.8% for the late cohort), while the contribution of sorting on μ_i changed very little (from 5.5% to 4.9%). On net, the overall contribution of sorting (column 4) has fallen substantially, from 21% percent to 12.8%. For men in the early cohort, the contribution of sorting is roughly half the value for women, but the gender gap is very small in the late cohort.[52]

[52]The contributions sorting on education, μ_i, and ω_{it} to the variance of $var(y\_ae_i)$ changes in part because the total contributions of these variables to $var(y_ae_i)$n changes across cohorts. For ease of reference, columns (5)-(7) in Table E.4 reproduce the contribution of these components to $var(y\_ae_i)$ from tables E.1-E.3.

8 Concluding Remarks

The family income stream that a person receives during their adult life depends on own earnings as well as on the earnings of other household members. The weights on the two are 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, but also for gender differences in the dynamics and distribution of family income.

To explore these issues, we combine a model of earnings for both men and women, a model of marital sorting, formation, and dissolution, a model of fertility, and a model of nonlabor income into a model of the family income of individuals over a lifetime. Given the complexity of each of the components and the challenge of combining them, we have had to make some compromises, but the payoff is large. The model enables us to estimate the dynamic responses of earnings and family income to labor market shocks, changes in marital status, education differences, and permanent wage heterogeneity—by gender and birth cohort. We also use the model to provide a detailed, gender- and cohort-specific accounting of the sources of variation in lifetime family income and other lifetime outcomes.

Although our work is related to several lines of research (which we discuss in some detail in the introduction), we do not know of another paper, structural or reduced form, that integrates individual labor market behavior, marriage, and fertility into a model of income dynamics and distribution. We are also the first (to our knowledge) to provide such detailed variance decompositions of family income and at the same time isolate the roles of marriage and sorting.

Three main themes deserve emphasis. The first concerns shocks. 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 1935–44, 1945–62, and 1964–74 birth cohorts that we study. The effects of divorce on family earnings and family income per adult equivalent became less negative for women and more negative for men. Gender differences in the effects of own unemployment and wage shocks on income for married individuals have also declined.

The second theme is that the large gender gap in the role played by marital sorting in the 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 decompositions of the variance (across individuals) of average annual family income over the adult life (ages 25 to 55). First, the gender difference in the importance of one's own permanent wage component narrowed substantially. For the early cohort, the variance contribution of the permanent wage component is 26.4% for men versus 13.8% for women, whereas for the late cohort the contributions are more similar (26.4% for men and 21.6% for women). The relative increase in the contribution of the permanent wage for women reflects at least in part the increased labor force participation of women 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 27.4% for the early cohort to 19.5% for the late cohort. For men, the corresponding values are 0.4% and 11.7%.

Much work remains to be done. First, lifetime family income is not utility, even after an adjustment for adult equivalents. Employment transitions and hours of work reflect consumer choices based on wages and the marginal utility of income, not just labor market constraints and shocks to health or the needs of children and relatives that restrict the time that can be devoted to market work. Marriage, and to a substantial degree fertility, are also choices. But one could improve on this using consumption data and perhaps use a cardinal utility function defined over children, leisure, and consumption to study the behavior of utility. A fully specified behavioral model based on optimizing behavior would be a natural but daunting step beyond the present paper.[53] Second, one would like to know more about how much of the income variation we study reflects uncertainty. This is important for assessing the role for self insurance through savings and for social insurance.[54] Third, much more could be learned about the effects of taxes and social insurance on the distribution of lifetime resources. One could add equations for taxes and transfers with parameters that depend on tax and transfer policy and examine how variation in policy over time or across states influences inequality. Fourth, we have focused on the resources of single adults and couples, but households have other adult family members. How have the transitions of adults into households with parents, adult children, and other non spousal members changed? How has that affected the dynamics and distribution of the resources an individual has access to over a lifetime? We leave these questions to future research.

[53]The framework used by Low et al. (2020) to study the effects of welfare receipt time limits on individual behavior and well-being has a number of the required elements .

[54]See Blundell, Pistaferri, and Preston (2008), Blundell, Graber, and Mogstad (2015), and Blundell, Pistaferri, and Saporta-Eksten (2016).

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

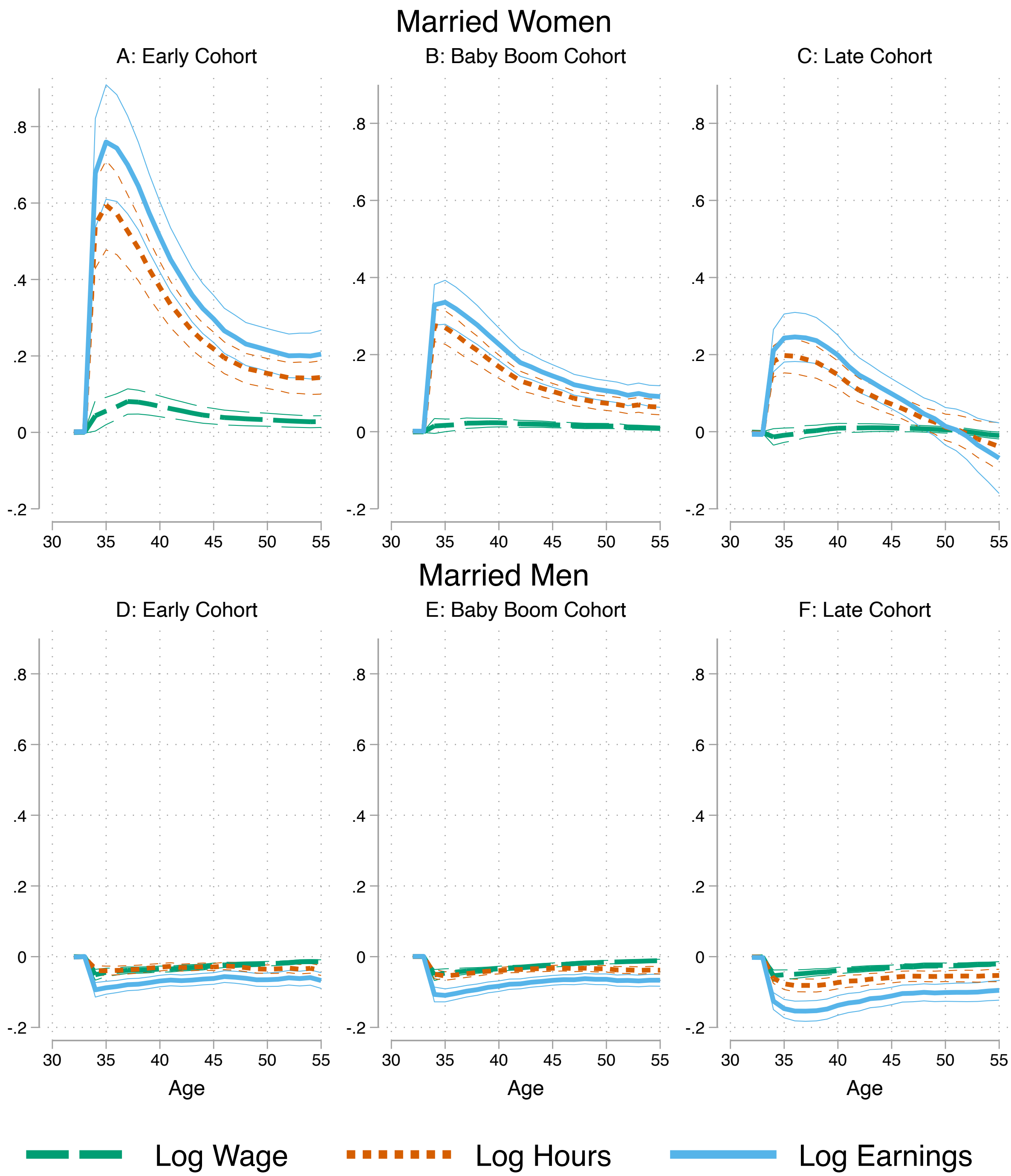


Figure 1 displays the effect of exogenously imposing a divorce shock on labor market variables. Panels A, B, and C focus on married women; D, E, and F show the results for men. The analysis is performed separately by cohort. Panel pair A and D show the results for those born from 1935 to 1944. B and E display the results for those born from 1945 to 1962, and C and F the results for those born from 1964 to 1974. 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 33 and have never experienced a divorce. We then perform the same simulation and calculation, but this time imposing that each married (and previously-never-divorced) individual is divorced at age 34. The presented estimates trace out the per-age difference in the average value of each variable between this second simulation and the baseline simulation. The thin lines display the 90% confidence interval and are calculated using 500 bootstrap replications.

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

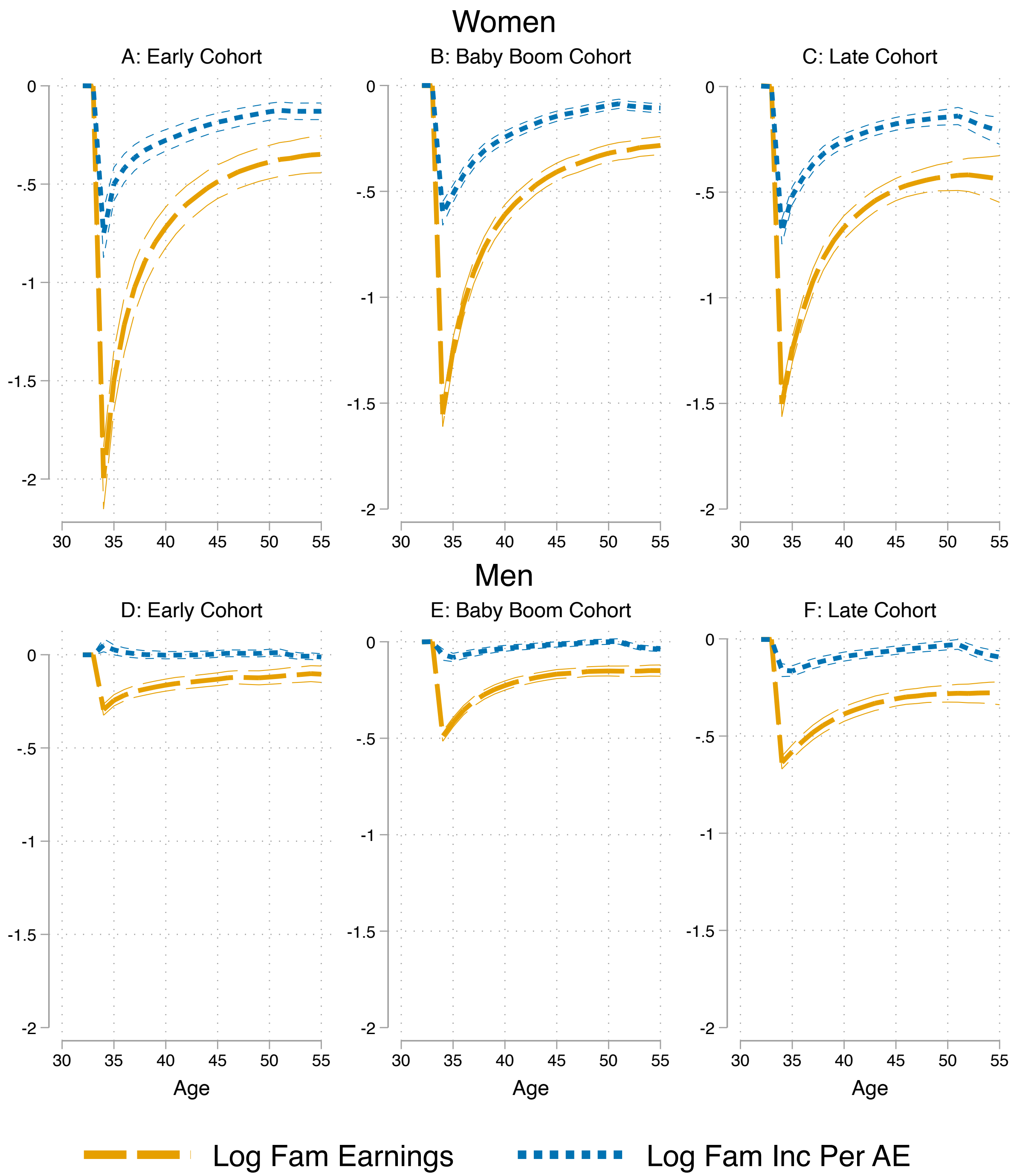


Figure 2 displays the effect of exogenously imposing a divorce shock on family earnings and family income per adult equivalent. Panels A, B, and C focus on married women; D, E, and F show the results for men. The analysis is peformed separately by cohort. Panel pair A and D show the results for those 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 1964 to 1974. To obtain the results, we use the same method as explained in the note to Figure 1.

Figure 3: Response of Earnings, Family Earnings, and Family Income Per Adult Equivalent to an Unemployment Shock

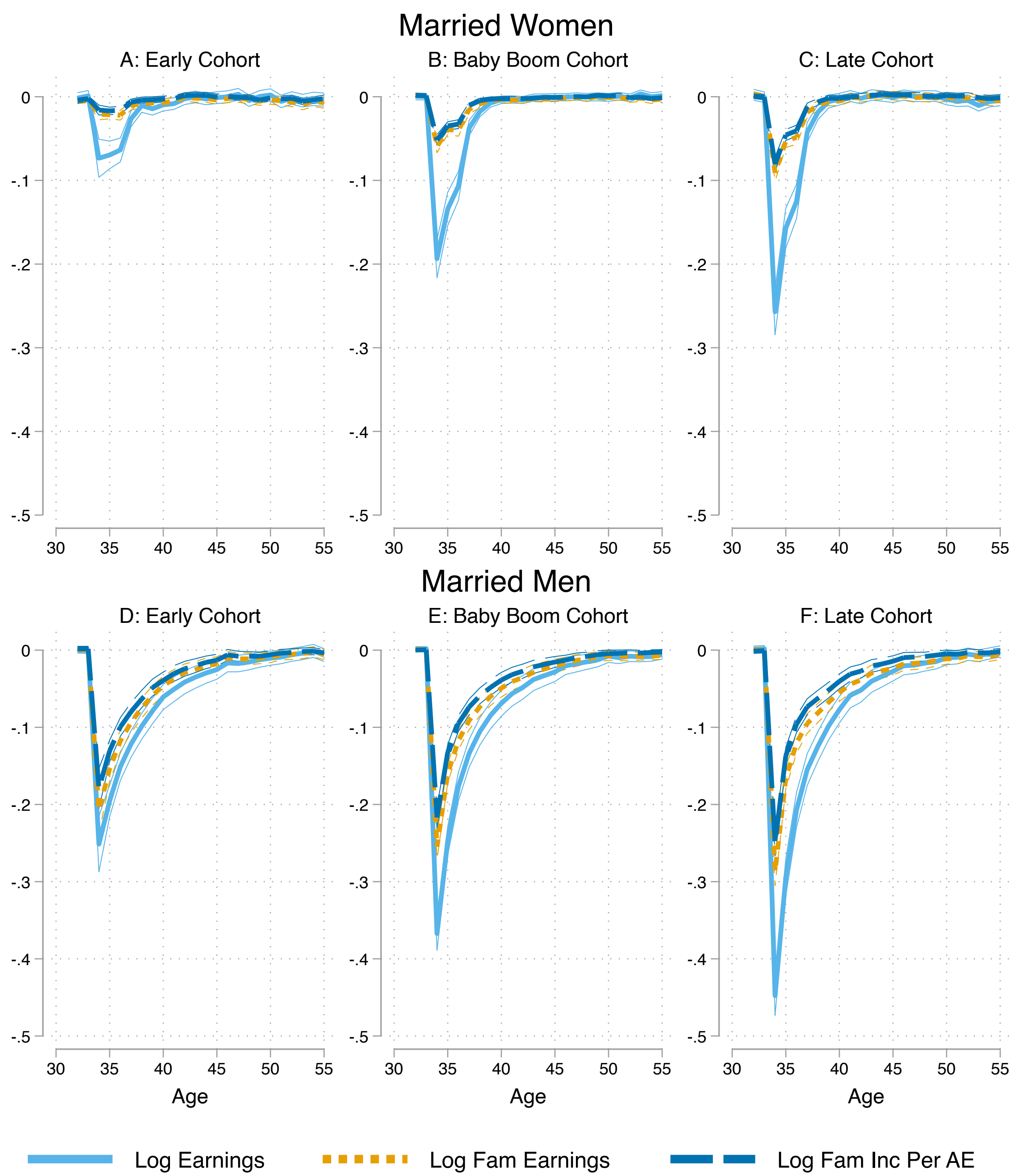


Figure 3 displays the effect of an exogenously imposed unemployment shock on married women and men. To obtain the estimates, we use the same method as explained in the note to Figure 1, but imposing instead that all married individuals in the labor force become unemployed at age 34.

Figure 4: Response of Earnings, Family Earnings, and Family Income Per Adult Equivalent to a Wage Shock

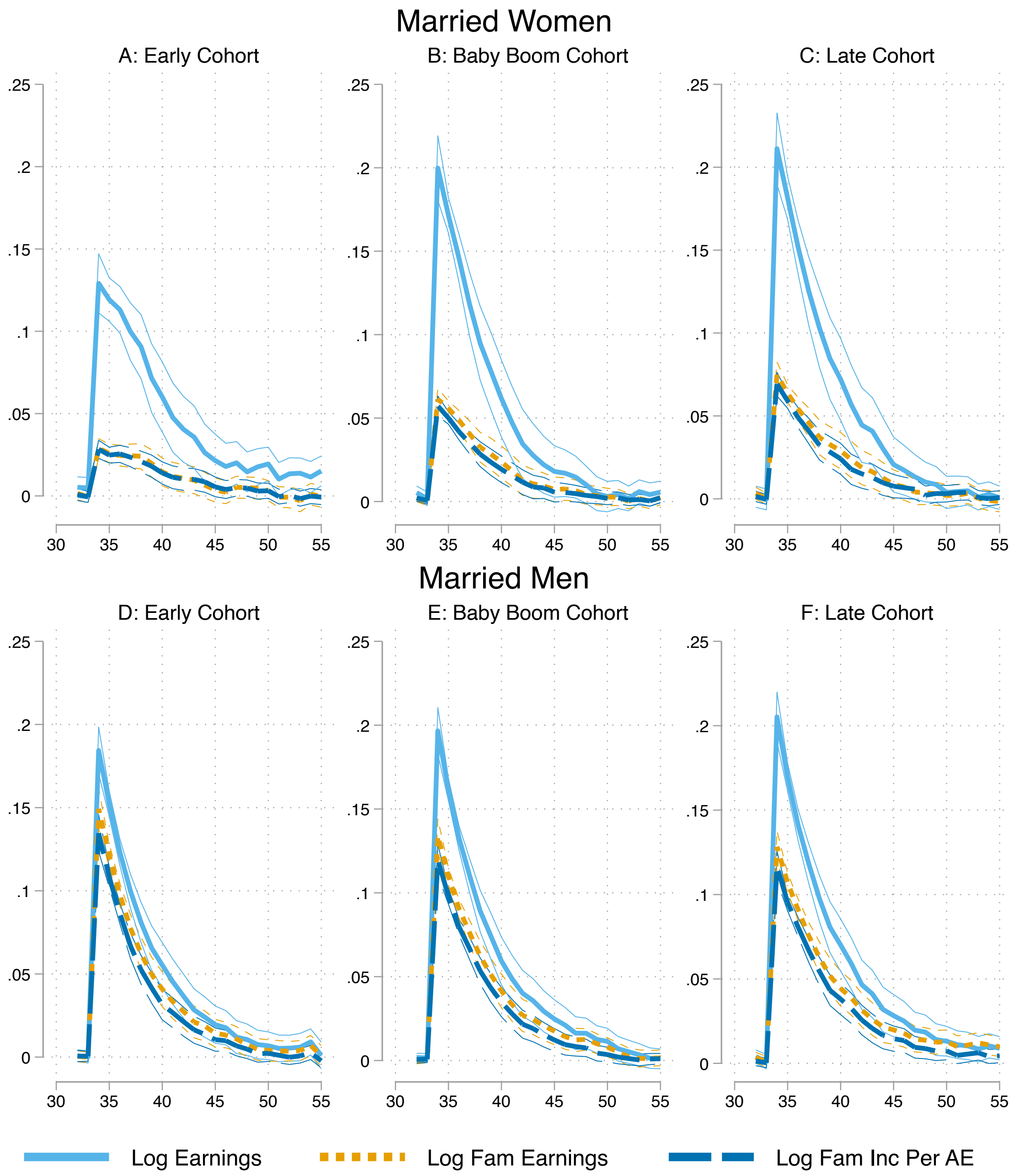


Figure 4 displays the effect of an exogenously imposed wage shock on married women and men. To obtain the estimates, we use the same method as explained in the note to Figure 1, but imposing instead a 1 SD increase in the autoregressive component of wages on all married individuals at age 34.

Figure 5: College - High School Gap in Earnings and Family Income Per Adult Equivalent

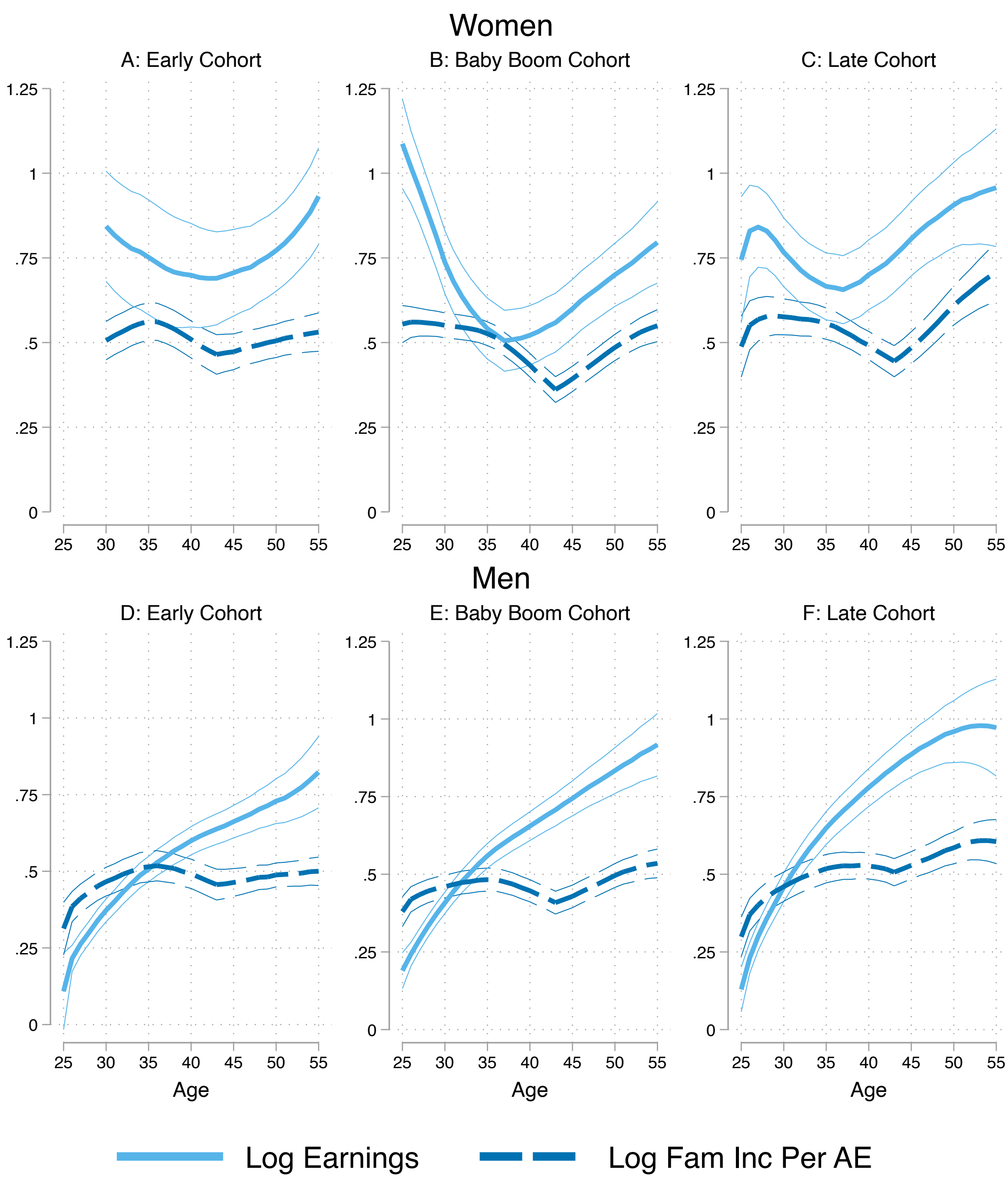


Figure 5 displays the difference in average log earnings and log family income per adult equivalent experienced by women and men at each age, imposing that all individuals have a college degree versus a high school education. To obtain the estimates, we first simulate the lives of 500 copies per PSID 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. The thin lines display the 90% confidence interval and are calculated using 500 bootstrap replications. We exclude ages 25–29 from the early cohort of women because we do not observe unemployment for most women in that birth-year-age group, which makes the estimates very noisy.

Figure 6: The Role of Marriage and Sorting in the College - High School Gap in Family Income Per Adult Equivalent

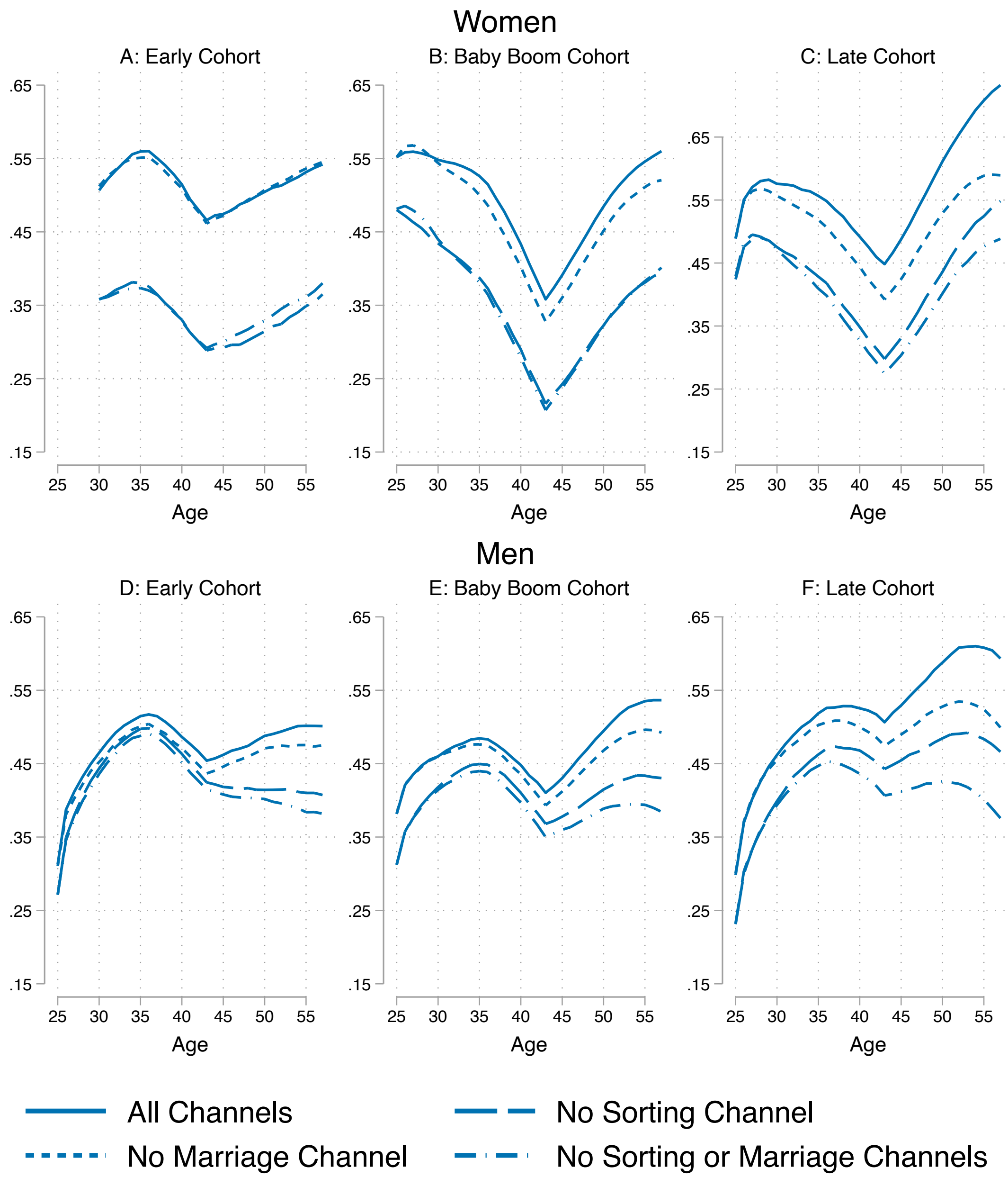


Figure 6 displays the role of marriage and sorting in explaining the effect of the college-high school gap in family income per adult equivalent. The solid lines are identical to the "Log Fam Inc Per AE" lines in Figure 5. That is, they trace out the college vs. high school gap in log family income per AE. In this figure, the difference between the solid line and the long-dash line should be interpreted as the role of marital sorting in explaining the effect of the education difference 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 between the two education groups in an environment where there is no sorting in the marriage market. Equivalently, we obtain the short-dashed "No Marriage" line 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 dot-dashed lines trace out the effect of the education difference when replacing both the sorting and marriage models with these alternative models.

Figure 7: Effect of Permanent Wage Difference on Earnings and Family Income Per Adult Equivalent

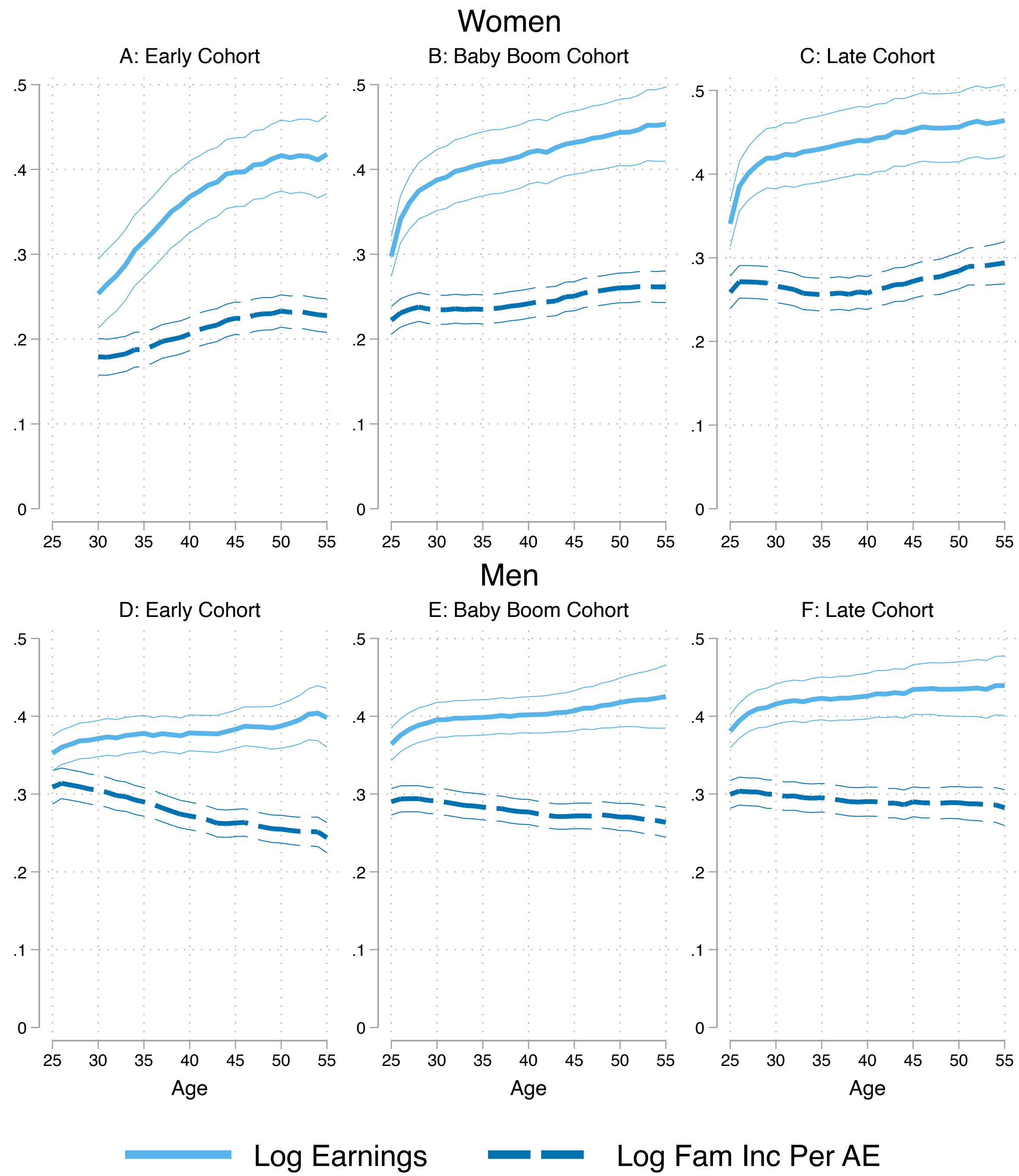
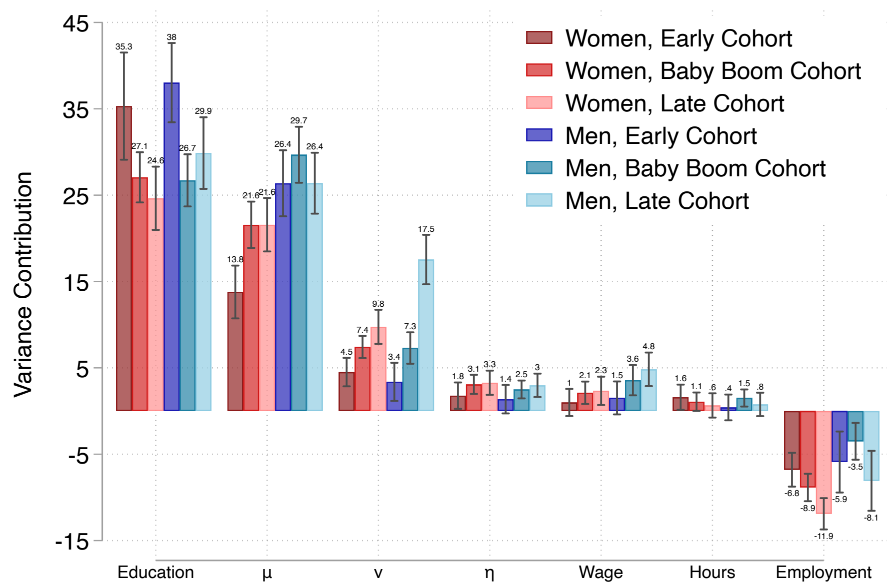


Figure 7 displays the difference in average log earnings and log family income per adult equivalent experienced by women and men, at each age, imposing that all individuals have a 1 SD higher permanent wage component, μ, throughout their lives compared to that drawn in the baseline simulation. To obtain 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. The thin lines display the 90% confidence interval and are calculated using 500 bootstrap replications.

Figure 8: Decomposition of the Variance of Lifetime Family Income Per Adult Equivalent

(a) Contribution of Own Characteristics



(b) Contribution of Spouse Characteristics

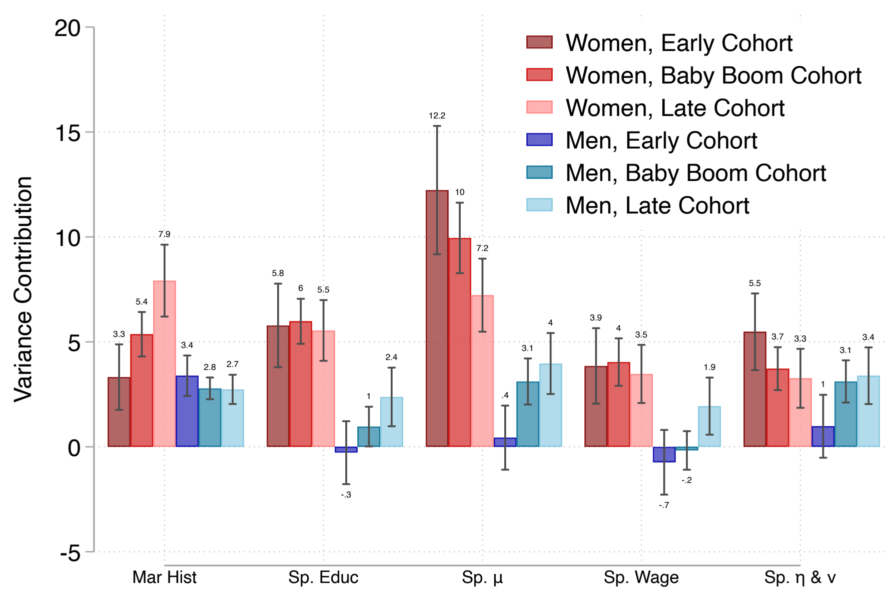


Figure 8 reports, by gender and birth cohort, the percentage of the variance of lifetime family income per adult equivalent explained by variation in different factors. Estimates are based on the simulation of 100 lives per PSID sample member. 90% confidence bands are displayed. Bootstrap standard errors are based on 500 draws of the estimation sample. μ, v, and η are the permanent components of wages, employment, and hours, respectively. "Wage" refers the initial draw and shocks to the autoregressive wage component and the i.i.d. wage shocks. Similarly, "Hours" refers to the initial draw and shocks to the autoregressive hours component and the i.i.d. hours shocks. "Employment" refers to i.i.d. shocks to employment status plus variation in initial employment conditional on number of children, marital status, and education. The point estimates are printed above the corresponding bar (below when the estimates is negative). 90% confidence bands are displayed. These are calculated using 500 bootstrap replications. Section 7.1 discusses the methodology.

Figure 9: Contribution of Own Characteristics to the Variance of Lifetime Earnings

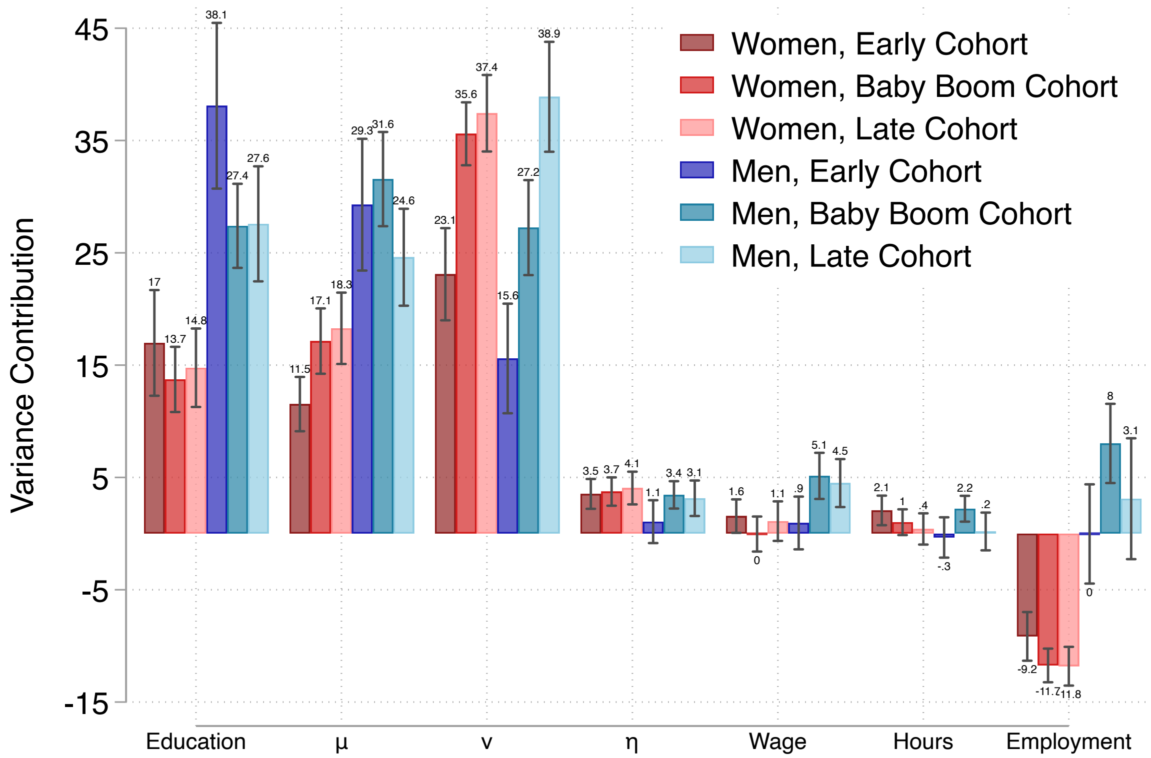


Figure 9 reports, by gender and birth cohort, the percentage of the variance of lifetime earnings explained by variation in different factors. The point estimates are printed on above the corresponding bar (below when the estimates is negative). 90% confidence bands are displayed. These are calculated using 500 bootstrap replications. See the notes to Figure 8 for more details. Section 7.1 discusses the methodology.