Econometrica Supplementary Material

SUPPLEMENT TO "CAREER AND FAMILY DECISIONS: COHORTS BORN 1935–1975"

(*Econometrica*, Vol. 87, No. 1, January 2019, 217–253)

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APPENDIX A: DETAILED DESCRIPTION OF THE DATA

A.1. *The CPS Data*

THE DATA WERE TAKEN from the Annual Demographic Surveys (March CPS supplement) conducted by the Bureau of Labor Statistics and the Bureau of the Census. This survey is the primary source for detailed information on income and employment in the United States. A detailed description of the survey can be found at: www.bls.gov/cps. Our data, for the years 1962–2015, were extracted using the IPUMS.

The sample is restricted to white civilian adults, aged 17–65, ignoring members of the armed forces and those who are institutionalized. In both Section 2 and in estimation, we define unmarried as including separated, widowed, divorced, and never married.

We divided the sample into five education groups: high school dropouts (HSD), high school graduates (HSG), individuals with some college (SC), college graduates (CG), and post-college degree holders (PC). In order to construct the education variable, we use the variable "educ" constructed by IPUMS. We use the schooling data from 17 to 30 in estimation, and assume no one attends school after age 30.

In order to construct couples, we kept only heads of households and spouses (i.e., no secondary families were used) and dropped households with more than one male or more than one female adult. We then merged women and men based on year and household id and dropped problematic couples (with two heads or two spouses, with more than one family, or with inconsistent marital status or number of children).

Nominal wages are deflated using the Personal Consumption Expenditure (PCE) index from NIPA Table 2.3.4 (https://fred.stlouisfed.org/release/tables?rid=53&eid=5039). Since wages refer to the previous year, we use the PCE for year $t-1$ to deflate observations in year t. All wages are expressed in constant 2009 dollars. The top-coded wage observations up until 1995 are multiplied by 1.75.

Our analysis focusses on five cohorts born within two years of the base years 1935, 1945, 1955, 1965 and 1975. Table A-I provides some descriptive statistics about each cohort.

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Previous versions of this paper were circulated under the titles "Wages and Employment of Married vs. Unmarried Individuals: Cohorts Born 1935–1975" and "Sources of Change in the Life-Cycle Decisions of American Men and Women: 1962–2014".

 https://doi.org/10.3982/ECTA14474

TABLE A-I

DESCRIPTIVE STATISTICS

Cohort	Obs.	Obs. per Year	% of College Graduate Mothers	Age Availability
1935	230,936	5633	6%	25–65
1945	381,075	7472	6%	17–65
1955	483,141	10,503	11%	17–61
1965	380,927	10,581	20%	17–51
1975	217,019	8347	27%	17–41

A notable difference between cohorts is the increase in mothers' education. For children in the 1935 birth cohort, only 6% of their mothers had a college degree (or beyond). But in the 1975 birth cohort 27% of the mothers had at least a college degree.

A.2. *Health Data and Health Transition Process*

The health data were taken from the IHIS (integrated health interview series) at Minnesota. The survey contains a subjective health index that takes on five values: Excellent, Very Good, Good, Fair, Poor. Empirically, we see that wages are not very different for those in the top three categories, but they are lower for those in fair or poor health. Thus, we decided to merge {Excellent, Very Good, Good} into a single category of "Good" health. This gives a health variable with three values: Good, Fair, and Poor. We then calculated the cumulative distribution of this new variable by cohort, gender, and age. (For more details, see http://www1.idc.ac.il/Faculty/Eckstein/EKL.html.)

We assume that each person starts out in good health at age 17. Health transitions are then governed by a multinomial logit function with Fair health as the omitted category:

$$P(H_t^j = k) = \begin{cases} \exp\left(\sum_{q=1}^{3} \chi_{kq} \cdot I[H_{t-1}^j = q]\right) / IV_{jt}^H & \text{if } k = 1, 3, \\ 1/IV_{jt}^H & \text{if } k = 2, \end{cases}$$

where k indexes health status, q indexes the coefficients, and $j = m, f$, and where

$$IV_{jt}^H = 1 + \sum_{k=1,3} \exp\left(\sum_{q=1}^{3} \chi_{kq} I[H_{t-1}^j = q]\right).$$

We estimated a separate health transition function for each cohort. The parameters of the health transition matrix for each cohort are listed in Table A-II.

A.3. *Social Welfare Payments*

Historically, social welfare benefits in the United States were heavily targeted toward single women with children, who were often viewed as a "deserving" group.[1] These benefits include AFDC/TANF, public housing, and child care subsidies (for women who work).

[1]See Katz, Michael B. (1989), "The Undeserving Poor: From the War on Poverty to the War on Welfare," Pantheon Books, New York.

TABLE A-II

HEALTH TRANSITION FUNCTION PARAMETERS[a]

		1935		1945		1955		1965		1975	
		Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.
Transition:											
Good to Good	χ_{11}	2.482	0.0246	2.560	0.1665	2.718	0.0698	2.813	0.0706	2.944	0.0750
Fair to Good	χ_{12}	−2.089	0.0418	−2.742	0.0557	−2.924	0.0056	−3.222	0.0119	−3.274	0.0116
Poor to Good	χ_{13}	−2.073	1.4873	−2.154	0.0683	−2.002	0.0725	−2.124	0.0603	−2.020	1.2081
Good to Poor	χ_{31}	−1.588	0.0472	−1.132	0.0835	−1.052	0.0866	−1.488	0.0439	−1.530	0.0771
Fair to Poor	χ_{32}	−2.324	0.0198	−2.198	0.0974	−2.241	0.0003	−2.227	0.0627	−2.159	0.0540
Poor to Poor	χ_{33}	1.905	0.0301	1.830	0.0127	1.754	0.0795	1.797	0.0178	1.706	0.0253

[a]Standard errors of the estimated parameters are reported in the columns labelled S.d..

They also include Medicaid, Foodstamps, and other programs. As Keane and Moffitt (1998) discussed, the determination of welfare benefits for single mothers is extremely complicated. This is because of the large number of programs, the fact that participation is a choice (and many women do not take up benefits), and the fact that program benefit rules are both individually complex and interact in complex ways. Indeed, welfare benefits cannot be expressed as a simple function of income (or labor supply) and children.[2]

Given this complexity, and the fact that welfare is not a key focus of our paper, we decided to specify the whole array of social benefits targeted at single mothers by a simple exogenous process. Thus, in equation (13), we assume single mothers are entitled to social welfare benefits according to the simple rule $cb_t(N_t)$ that only depends on number of children. We estimate this function from CPS data, and treat it as exogenously given (but varying by cohort) when estimating our structural model.[3]

Specifically, we measure welfare benefits in the CPS using the variable "INCWELFR" (i.e., income from welfare) in IPUMS. This indicates how much pre-tax income (if any) the respondent received during the previous calendar year from various public assistance programs commonly referred to as "welfare." We adjust for inflation using the PCE (just as we did with wages). We then run a regression of the real annual welfare payment as a function of the number of children using the subsample of single mothers with children who take up benefits. We run the regression separately for each cohort. Based on the subsample of unemployed women, we obtained the results listed in Table A-III for annual welfare payments for single mothers (2009 prices).

The key pattern in the data is the fact that benefits for single mothers peaked in generosity in the late 1970s, and steadily declined thereafter (with the decline accelerating in the early 1990s).[4] This is reflected in the lower benefits available to the 1965 and especially the 1975 cohorts. The 1975 cohort would have reached working age under the

[2]Put more formally, Keane and Moffitt (1998) showed that the budget constraints faced by single women with children in the U.S. are both endogenous (due to program participation decisions) and highly complex. To make matters worse, rules differ substantially by state.

[3]In our model, the $cb_t(N_t)$ process captures a key determinant of the threat point for married women with children when considering divorce.

[4]See Moffitt, Robert (1992), "Incentive Effects of the US Welfare System: A Review," *Journal of Economic Literature*, 30:1, 1–61.

TABLE A-III

WELFARE PAYMENTS AS FUNCTION OF CHILDREN

	1935	1945	1955	1965	1975
Single parent with 1 child	4318	4749	4531	3801	2711
Each additional child	1517	1180	975	862	764

far less generous rules that went into effect in the mid-1990s. If we do not condition on unemployment we obtain, instead, the figures:

	1935	1945	1955	1965	1975
Single parent with 1 child	4041	4394	3762	3337	2469
Each additional child	1430	1118	1082	865	743

Note that conditioning on unemployment only slightly reduces the average levels of benefits, and does not alter the overall patterns. There are a number of reasons it makes little difference. First, the employment rate of single mothers with children is quite low. Second, many of those who work still qualify for a variety of benefits, either because they have low wage rates, or because some benefits (like public housing) have very low taper rates on earnings, such that working women still receive them, and conversely, some benefits (like child care subsidies) only arise if one starts working. Third, even among the unemployed who are eligible for benefits, a significant fraction do not take them up.[5]

APPENDIX B: TAXES

Given the gross income associated with any particular wage offer and labor supply choice, we calculate the household's tax liability based on the federal tax rules in effect in the relevant year. This depends on whether it is a single household (subject to the individual tax schedule) or a married couple (subject to the joint tax schedule), as well as the number of dependents. We also account for the earned income tax credit (EITC). To calculate the tax liability of a given household or individual in any particular year, we collected historical data from 1950 to 2017 from the following sources:

1. Federal income tax rate history (https://taxfoundation.org/federal-tax/individual-income-payroll-taxes)
2. Standard deduction history (http://www.taxpolicycenter.org/statistics/standard-deduction)
3. Personal and dependents exemption (https://www.irs.gov/publications/p17/ch03.html)

[5]Many women who qualify for benefits do not take them up fully, either by choice or because some benefits (housing) are rationed. Keane and Moffitt (1998) found that many eligible non-working women who do not take up welfare benefits have access to significant non-welfare sources of non-labor income, such as SSI, alimony, child support, widow benefits, etc. Hence, we view $cb_t(N_t)$ for those who do take up benefits as a reasonable proxy for the full range of non-labor income to which a typical single women with children would be entitled.

4. Earned income tax credit parameters (http://www.taxpolicycenter.org/statistics/eitc-parameters)

Using these parameters, we programmed a "tax calculator," where the inputs are gross income, marital status, number of children, and the year, while the output is net income. The program uses the actual tax brackets and marginal tax rate, the full structure of the EITC, and the number of deductions and exemptions (which varies by the marital status and the number of children).[6] The tax brackets and marginal rate that were used in the model, together with the full historical data on EITC, deductions, and exemptions, can be found on the website http://www1.idc.ac.il/Faculty/Eckstein/EKL.html.

To simplify the solution of the dynamic programming problem, we assume that agents in the model have perfect foresight about future tax rules. Furthermore, for years beyond 2017, households assume that tax rules will remain fixed at the 2017 values.

There are two possible alternative approaches to modeling expectations: First, we could assume agents are myopic, and every tax rule change is a surprise. This is computationally infeasible, because households would face a new dynamic programming problem each year. Second, we could assume a tax rule generating process, as in Keane and Wolpin (2010). This is also infeasible here, as lagged tax rule parameters become state variables. Perfect foresight is the simplest approach.

Finally, note that we solve the model for five cohorts born in exactly 1935, 1945, etc. When simulating data for hypothetical agents in the model, we use the annual tax rules for persons born in exactly those years. But in the actual data, we classify people within a 5-year birth window as part of the same cohort. In estimation, we ignore the fact that each data cohort is a mixture of people from five adjacent birth years who face slightly different tax rate histories.

APPENDIX C: ADDITIONAL FIGURES

Figure C1 plots employment rates by cohort and age. In addition to the five cohorts used in estimation, we also show the 1925 and 1985 birth cohorts. Results for married women, unmarried women, married men and unmarried men are shown in panels A, B, C and D, respectively.[7]

One striking pattern revealed by Figure C1 is there are no substantial differences across cohorts in employment rates by age for unmarried women, or for either married or unmarried men. In contrast, the employment rate increased sharply over cohorts for married women.

For married women the difference in behavior between the 1955 cohort and earlier cohorts is particularly striking. Two changes are notable: First, the employment rate in the early 20s is several points higher. Second, and more importantly, employment does not decline in the mid-to-late 20s. Married women in the 1955 cohort remain in the labor force during their prime childbearing years to a much greater extent than did those in the 1945 cohort. There is also one notable similarity between the 1955 and 1945 cohorts: Despite the employment rate gap of 17 points at age 29, the employment rate of the 1945 cohort catches up later, so that from ages 40 to 50 it is only a few points lower than the 1955 cohort (i.e., about 70% vs 65–67%).

[6] To simplify the program, we assume the maximum number of tax brackets is 10. For some years before 1986, there were more than 10 tax brackets, so we unified similar tax brackets, that is, instead of having two tax brackets, one with a 49% marginal tax rate and one with 50%, we unified the two into one tax bracket.

[7] Here we combine the divorced and single categories into "unmarried" as they behave very similarly.

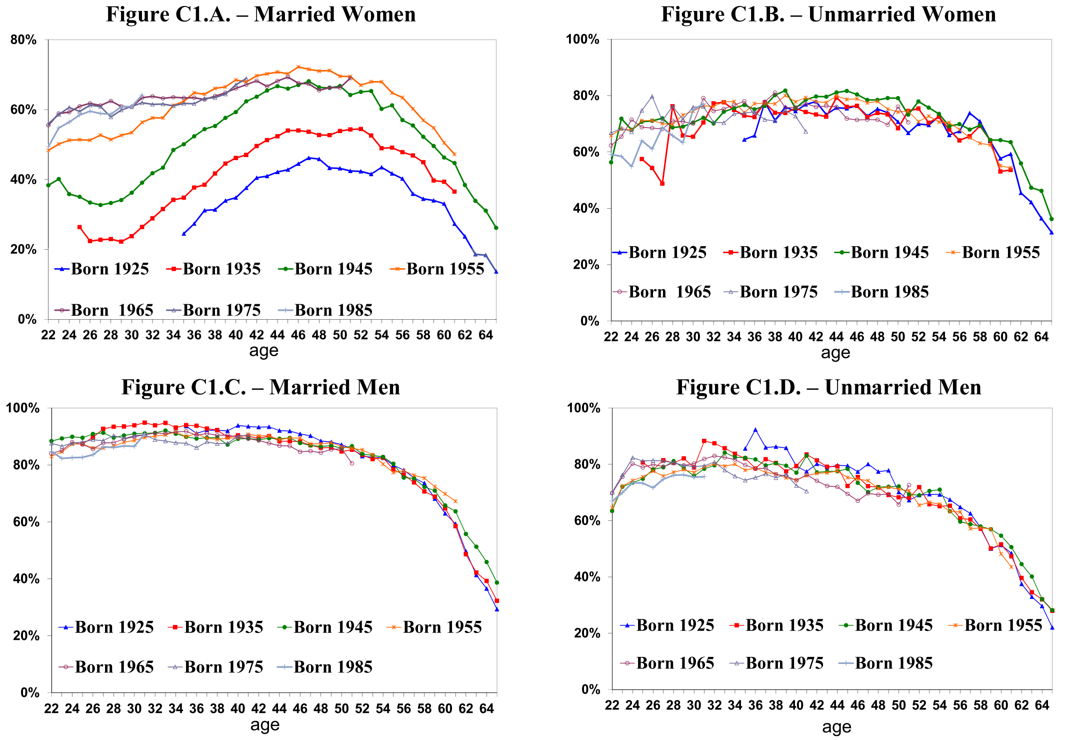

FIGURE C1.—Male and female employment rates by age and cohort. *Note*: The fraction employed of the Caucasian population aged 22–65. We define "employment" as working at least 10 hours a week. Married includes married with spouse absent. Unmarried is defined as Separated, Widowed, Divorced, and Never married. Data availability: cohort 25: ages 35–65. Cohort 35: ages 25–65. Cohort 45: ages 22–65. Cohort 55: ages 22–61. Cohort 65: ages 22–51. Cohort 75: ages 22–41. Cohort 85: ages 21–31.

It is also notable that in the 1955 to 1985 cohorts the employment rates (by age) for married women are very similar. There is a slight increase at young ages from the 1955 to 1965 cohorts, but from 1965–1985 there is great stability. Thus, the historic increase in married womens' employment was essentially complete by the 1965 cohort.

Figure C2 shows how education levels have changed by gender and marital status over time. Education is grouped into 5 levels: high school drop-out (HSD), high school graduate (HSG), some college (SC), college graduate (CG) and post-graduate (PG).

The key fact revealed by panel A of Figure C2 is that college and post-college education rose much more quickly for married than unmarried women. In 1964, only 7% of married women had a college degree or more, compared to 10% for unmarried women. By 2014, this pattern had reversed, and 36% of married women had a college degree or more, compared to 28% of unmarried women. The percentage of college graduates among married women passed that among unmarried women in 1993.

Figure C2 panel B plots the education distribution for men over time. A striking fact is that in 1964 the education levels of married and unmarried men were almost identical. Roughly 47% of both married and unmarried men were high school drop-outs. And 13% of both married and unmarried men had a college degree or more. Over time, education has increased substantially for men. But, similar to women, education levels have increased much more for married men than unmarried men. By 2014, roughly 35% of

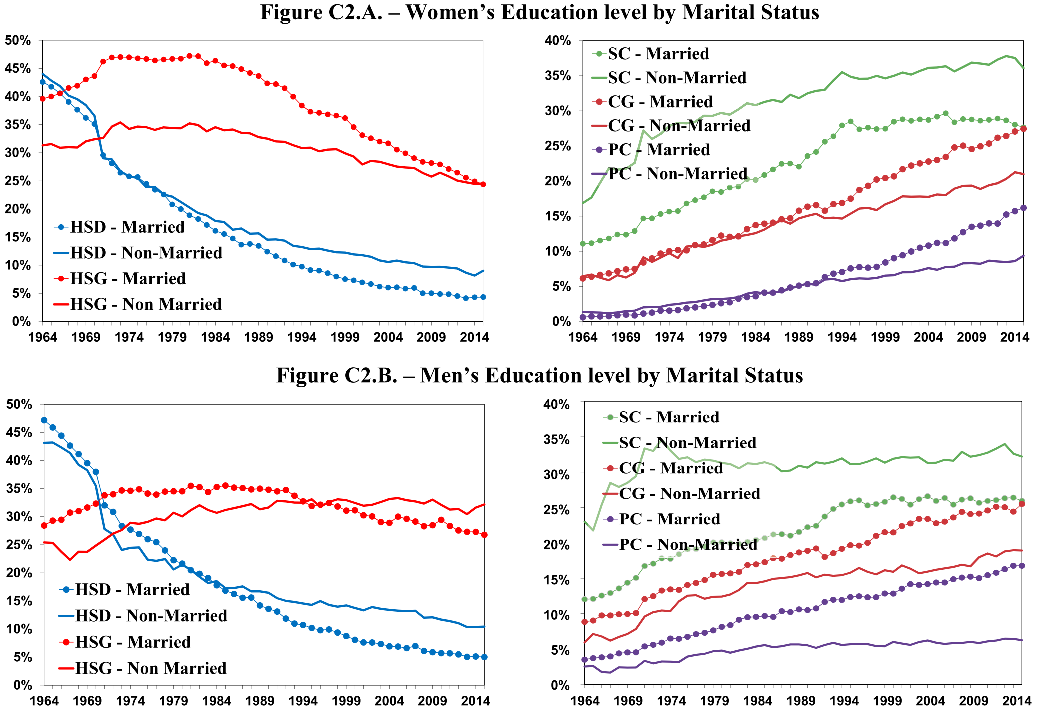

FIGURE C2.—Education and marital status over time. *Note*: The fraction of individuals at each education level. Caucasian population aged 22–65. Married includes married with spouse absent. Unmarried is defined as including separated, widowed, divorced, and never married.

married men had a college degree or more, compared to only 24% of unmarried men. Finally, note that, by late in the sample period, women were more educated than men.

APPENDIX D: WAGES BY MARITAL STATUS/COHORT, AND ESTIMATES OF MINCER WAGE FUNCTIONS

Table D-I reports the differences in average wages between married and unmarried women by cohort. In the 1935 cohort, the gap was -12%, but it is eliminated in the 1965 cohort, and becomes $+8\%$ in the 1975 cohort. To get a sense of the importance of education in explaining these changes, we also report the so-called "marriage wage gap." This is conventionally defined as the coefficient on a marriage dummy included in a standard Mincer earnings equation, as in

$$\ln(W_{it}) = \beta_0 + \beta_1(age\text{-}school)_{it} + \beta_2(age\text{-}school)^2_{it} \\ + \beta_3 HSG_{it} + \beta_4 SC_{it} + \beta_5 CG_{it} + \beta_6 PC_{it} + \beta_7 M_{it} + u_{it}.$$

Here i denotes person, t denotes year, and $school_{it}$ is total years of schooling, so $(age\text{-}school)_{it}$ is "potential" labor market experience. Education is captured by dummy variables for high school graduate (HSG), some college (SC), college graduate (CG), and post-college (PC). High school dropout (HSD) is the omitted group. The coefficient β_7 on the marriage indicator M_{it} captures the conditional correlation of wages with marriage. We estimated such regressions using the data for each of the five cohorts for both men and women. Table D-I reports the coefficients on the marriage dummies.

TABLE D-I
WAGES BY MARITAL STATUS AND COHORT

	1935	1945	1955	1965	1975
Women					
Average Wages—Married	21.9	26.7	31.3	37.3	43.9
Average Wages—Unmarried	24.6	29.4	33.3	36.6	40.5
Married/Unmarried Difference	−12.0%	−10.2%	−6.5%	1.8%	7.8%
Marriage Wage Gap	−8.9%	−6.8%	−1.7%	2.0%	5.2%
Men					
Average Wages—Married	41.3	47.8	48.3	54.0	57.6
Average Wages—Unmarried	34.2	41.0	39.6	42.7	46.4
Married/Unmarried Difference	17.3%	14.2%	18.0%	20.8%	19.4%
Marriage Wage Gap	19.7%	18.7%	19.5%	19.7%	18.3%

Consider first the results for women. In the 1935 cohort, married women earned 9% *less* than unmarried women (conditional on "potential experience" and education). But in the 1975 cohort, the wages of married women are 5% *higher* than those of unmarried women. Thus, the marriage wage gap turned from highly negative to highly positive in just two generations (40 years). Recall that for raw wages, the shift was from −12% to +8%. Thus, changes in education and potential experience can only account for about 30% of the change.

The bottom panel of Table D-I reports similar results for men. In contrast to women, the marriage wage gap and mean wage differences changed little over the past 40 years. In particular, the marriage wage gap was 20% for the 1935 cohort and 18% for the 1975 cohort. These patterns are consistent with Figure 2, which shows that aggregate real wages of married men, single men, and single women all grew at similar rates (1.0–1.3% annually), while wages of married women grew at a much faster rate (1.8% annually).

APPENDIX E: TECHNICAL NOTES ON THE SOLUTION OF THE MODEL

E.1. *The Marriage Market*

As noted earlier, we assume all married couples are equal in age. We do this for the following reason: Say we back-solve the DP problem from age T. Further suppose a person at age T may receive marriage offers from either: (i) people who are also age T, or (ii) people who are younger. In the case of an offer from a potential partner who is also age T, we can easily calculate the expected value of the marriage state at age T for both parties. We can then compare this to the expected value of being single. Then, by comparing the married and single value functions, we can determine if the marriage will form. These calculations are straightforward because there is no future $(T+1)$ for either party, so it is a static problem.

On the other hand, suppose a person of age T receives a marriage offer from a younger person. To be concrete, say the latter is age $T-1$. Then we run into a problem—that is, because we are still in the process of solving for the age T value functions, we do not yet have the information we need to calculate age $T-1$ value functions. As a result, we cannot determine the value of the match for the person of age $T-1$. Hence, we cannot determine if the match will form. Given this conundrum, it appears to be essentially impossible to solve a dynamic marriage market model (using the method of back-solving) if people can get offers from younger people.[8] We resolve this problem by assuming couples are equal in age.

An alternative approach would be to drop chronological age from the state space entirely. For instance, one could replace chronological age by biological age, and assume this is a state variable that evolves stochastically—that is, biological age could go up, down, or stay the same from t to $t+1$, depending on what happens to a person's health. We might assume that when a person reaches chronological age $T+1$, they die with certainty. Nevertheless, this would be an infinite horizon problem, because even a person of biological age T has a positive survival probability. The solution to such a model would be obtained by solving a fixed-point problem, not by back-solving.

In this type of model, a person of biological age t could potentially receive marriage offers from people of any biological age from $t = 1, \dots, T$. This no longer creates a problem, because the model would be solved using a fixed-point method, rather than by back-solving. So, if we replace chronological age by biological age in the state space, the fact that a person may receive marriage offers from a younger person creates no computational problem.

We decided to not adopt this approach for the following reason: If chronological age is not in the state space, it seems difficult to generate the observed similarity of ages within married couples. We could obviously introduce a preference for marrying someone of similar biological age. But the distribution of health, which is the main signal of biological age, is rather stable across different chronological ages in our data, at least until people reach their 60s and 70s. Thus, even a strong tendency to marry people of similar biological age tends to leave us with a counterfactually large dispersion of chronological ages within couples. Better data on markers for biological age could resolve this problem. For now, we decided that an assumption of equal chronological ages within couples would be simpler to implement, and would provide a reasonable approximation to the data, as most couples are fairly close in age.

E.2. *The Number and Ages of Children*

The state space becomes extremely large if we follow the ages of children. Therefore, we introduce, in equation (5), dynamics in the utility of home time following the birth of a new child. If children only entered the model through their effect on tastes for leisure, then neither $N(t)$ nor the ages of children would be state variables (as μ_{jt} in equation (5) is a sufficient statistic for all past fertility). However, $N(t)$ also enters our model through the budget constraint (the cost of children), welfare rules, tax rules, and the cost of divorce. These quantities depend only on $N(t)$, not on the ages of the children. So the addition of these features requires $N(t)$ to enter the state space. Nevertheless, these features also require a forward-looking agent to foresee when a child will reach age 19, at which point they leave the household and no longer enter payoffs or constraints. Unfortunately, this requires the agent to keep track of the age of the child. And this would render the state space intractably large.

To deal with this, we adopt the position that (i) changes in tastes for leisure when young children arrive is a first-order problem for female labor supply that is captured by μ_{jt}, while (ii) relative ages of older children have only a second-order effect on labor supply (e.g., labor supply behavior does not vary much as children age from, say, 8 to 18, a view that prior literature supports). Thus, we choose to ignore child ages in the state space,

[8]Note that making the maximum age of marriage less than T would not change the nature of this problem.

which is tantamount to assuming that, conditional on tastes for leisure μ_{jt}, households with the same $N(t)$ will behave in the same way, ceteris paribus, regardless of the children's ages. This means that, in solving the DP problem, we need only solve over a grid of μ_{jt} and $N(t)$ values at each age. Of course, when forward simulating the model, we do keep track of the child ages. Thus, for example, if an only child reaches 19, the household ceases to use the value functions defined for $N = 1$, and shifts to the value functions defined for $N = 0$. Thus, there is a structural break in household behavior when the children leave home.

APPENDIX F: DETAILS ON THE ESTIMATION METHOD

The estimation method is the Method of Simulated Moments (MSM), as proposed by McFadden (1989) and Pakes and Pollard (1989). The method involves finding the parameter vector φ that minimizes the distance between the actual data and data simulated from our model. Let d_r denote a statistic from the actual data, and let $d_r^s(\varphi)$ be the corresponding statistic calculated in the simulated data, and assume we fit the model to $r = 1, \dots, R$ statistics. We then construct moments of the form

$$m_r^s(\varphi) = \left[d_r - d_r^s(\varphi)\right] \quad \text{for } r = 1, \dots, R. \tag{F1}$$

The vector of simulated moments is given by $g'(\varphi) = [m_1^s(\varphi), \dots, m_R^s(\varphi)]$. We minimize the objective function $G(\varphi) = g'(\varphi)Wg(\varphi)$ with respect to φ, where the weighting matrix W is a diagonal matrix consisting of the inverse of the estimated variance of each moment (from a first step). We minimize $G(\varphi)$ with respect to φ using the Simplex algorithm.

Given the solution of DP problem (see Section 4) at a candidate value for φ, we simulate data from the model as follows: First, we set the initial conditions at age 17. All agents start with zero work experience, 10 years of education, good health, and unmarried. We draw parent education, the skill type, and the taste for work type for each hypothetical person, using the distributions implied by the data and equations (5) and (23). We simulate hypothetical data for 1000 men and 1000 women for each cohort. The only difference between cohorts is the initial conditions, specifically, the distribution of parent education, the stochastic process for health, and the income tax and welfare benefit rules.

Given the initial conditions, we simulate hypothetical life-cycle histories from age 17 until the terminal period.[9] In order to simulate forward, we must draw, for each person i in each period t, the job offer, a wage shock, a taste for leisure shock, a health realization, a taste for marriage shock (if married), and the realization of a potential partner (if single).[10] For singles, we also draw a taste for school shock. And for single women and married couples, we draw tastes for pregnancy. Conditional on these draws, the model generates simulated choices and outcomes for all the observed endogenous variables: education, employment, marital status, children, wages, and health.

In order to form the d_r and $d_r^s(\varphi)$ that enter (F1), we construct, for each cohort, a set of statistics from both the simulated and actual data that summarize key predictions of the model. These include (a) the schooling distribution by gender, (b) employment rates

[9]As we note in Sections 3.6 and 5 of the text, only the 1935 and 1945 cohorts are actually observed through age 65, but we decided not to use the data from ages 62–65 in estimation. We chose to fit our model only to data up through age 61 to avoid having to model the possible early receipt of Social Security at age 62.

[10]We first draw whether a marriage offer is received. If it is, we then draw the match quality and characteristics of the potential partner: schooling, experience, ability, tastes for work, children from previous relationships, health, parents' education, and whether employed in the previous period.

by gender, marital status, and age, (c) average wages conditional on gender, education, marital status, and age, (d) marriage and divorce rates by age, (e) number of children by age/marital status, and (f) the pattern of assortative mating by education of the partners. We list the moments in detail in Appendix H.

We compute standard errors numerically. Calculation of standard errors is complicated by non-smoothness of the objective function, so we use "long baseline" numerical derivatives, which was one suggestion in McFadden (1989).[11] Specifically, we compute the numerical derivative with respect to each of the parameters, φ_p using the five-point stencil formula with a long baseline:[12]

$$f_{\varphi_p} = \frac{-f(\varphi_p + 2\varepsilon_p) + 8f(\varphi_p + \varepsilon_p) - 8f(\varphi_p - \varepsilon_p) + f(\varphi_p - 2\varepsilon_p)}{12\varepsilon_p},$$

where f is a vector of the squared moments divided by their weights: $[d_r - d_r^s(\varphi)]^2/W_r$, and ε_p is equal to $0.01 \cdot \varphi_p$ (a rather large gap). Note that the use of baseline intervals of different length is a form of Richardson extrapolation, which is in turn a bootstrapping method. Given the numerical derivatives, we compute the covariance matrix using the outer product approximation to the Hessian.

APPENDIX G: TERMINAL VALUE FUNCTION SPECIFICATION

As we discuss in Section 3.6 of the text, we wished to avoid the complications of modeling Social Security and the accumulation of retirement savings. Given the already great complexity of our model, including the additional state and choice variables required to model Social Security benefits and retirement behavior would be infeasible.[13] Instead, we employ the technique of setting a "terminal value function" $V^j_{T+1}(\Omega_{j,T+1})$ at a pre-specified age T beyond which we do not attempt to structurally model behavior, as in Keane and Wolpin (2001).

Because the "normal" Social Security retirement age is 65, and a large fraction of workers do retire by that age, we decided to fix the terminal period T in our model at age 65. After that point we assume that everyone must retire.[14,15] Of course, people can choose

[11] We admit that long baseline derivatives can be coarse approximations. Thus, Keane (1994) argued for use of smooth simulators (like GHK) instead. Unfortunately, smoothing is difficult given the complexity of our model. Given the structural parameters are of secondary interest here (which is why they are relegated to Appendix J), the standard errors are obviously of secondary interest as well, so we did not view smoothing as essential.

[12] See Abramowitz, Milton; Stegun, Irene A. (1970), *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*, Dover, 9th Edition. Table 25.2.

[13] For a recent paper that models Social Security and retirement behavior in detail, while also considering labor supply and human capital accumulation, see Keane, M. and N. Wasi (2016), "Labour Supply: the Roles of Human Capital and the Extensive Margin," *The Economic Journal*, 126(592), 578–617. That paper considers only men and does not incorporate marriage or fertility decisions.

[14] The "normal" Social Security retirement age is that age at which one can begin receiving full benefits. In fact, for our five cohorts, the "normal" age for claiming Social Security (SS) benefits was gradually increased from 65 for the 1935 cohort to 66 for the 1945 cohort to 67 for the 1965 cohort. We ignore this change because age 65 has remained a "focal point" for retirement decisions in the U.S. for two reasons: (i) it is the age for Medicare eligibility, and (ii) it is still a common age for private pension eligibility.

[15] It is worth noting that for all our cohorts, workers could also opt to receive "early" Social Security benefits at age 62, subject to a penalty in the form of a reduced benefit level. We ignore this option in our model (i.e., we ignore any change in the structure of the model at age 62 that arises because this option is available). To avoid any bias this might cause, we only use data up through age 61 in estimating the model.

TABLE G-I
TERMINAL VALUE FUNCTION PARAMETERS[a]

	Women		Men	
	Parameter	S.d.	Parameter	S.d.
Individual education is HSG	10.340	4.102	22.585	0.073
Individual education is SC	29.719	8.965	28.044	0.054
Individual education is CG	28.026	3.149	27.699	0.011
Individual education is PC	51.633	7.155	27.968	0.282
Individual experience	22.726	3.538	5.723	0.045
Partner education is HSD	−7.355	2.705	7.650	0.386
Partner education is HSG	10.002	3.990	11.259	0.494
Partner education is SC	17.344	4.979	14.664	0.683
Partner education is CG	55.865	9.837	22.623	0.378
Partner education is PC	37.632	5.739	24.408	0.432
Partner experience	11.716	4.831	5.992	0.960
The individual worked in $T-1$	17.925	0.051	9.371	3.450
Marital status	104.301	25.249	67.706	0.558
# of kids	13.328	7.747	2.025	1.241
Match quality if married	19.679	10.859	6.319	3.437
# of kids if married	6.715	3.956	3.697	1.893

[a]Standard errors of the estimated parameters are reported in the columns labelled S.d..

to stop working earlier if desired. To reduce computational burden, we assume the terminal value function $V^j_{T+1}(\Omega_{j,T+1})$ at $T = 65$ is a simple function of the state variables in $\Omega_{j,T+1}$.

Specifically, the terminal value function is a linear function of the state variables (dated at the end of period $T = 65$) listed in Table G-I. It includes state variables of the spouse if one is married. Table G-I presents the estimates of the terminal value function parameters, which were obtained separately for men and women as part of the benchmark model.

An interesting feature of the terminal value function is that work experience and education (both own and spousal) are highly significant. In our model, these variables play no role other than to determine the distribution of offer wages. Thus, as agents cannot work past age 65, there is no direct reason for them to value these quantities. The only rationale for why agents in our model would care about work experience and education after age 65 is that they proxy for retirement assets. Thus, as we argue in Sections 3.1, 3.6 and 6.4, the terminal value function accounts for agents' concern about retirement savings in a reduced form way.

Stated another way, the fact that V_{66} is increasing in work experience adds an extra return to labor supply that is not captured by the wage rate wage alone. Presumably, this value arises because labor supply also causes workers to accumulate both Social Security benefits and private pension benefits. If the terminal value function did not incorporate this added value of work, then labor supply in our model would drop off (too) precipitously before the $T = 65$ terminal period (as older workers would not need to be concerned about accumulating retirement savings).

Not surprisingly, the terminal value function estimates indicate that people also value marriage, quality of marriage, and children after age 65. The latter implies that children continue to generate utility for parents even after they leave the household at age 18.

TABLE H-I
AGE PROFILE BY COHORT

	1935	1945	1955	1965	1975
Age Range	25–65	17–65	17–61	17–51	17–41

APPENDIX H: MOMENTS FIT IN THE MSM ESTIMATION

The moments we can use in estimation depend on the availability of data for each cohort. As we report in Table H-I, we observe different cohorts over different age ranges. Notice that only the 1945 cohort has complete data from age 17 to 65. We do not have data for the 1935 cohort prior to age 25, while for the 1955, 1965, and 1975 cohorts, the data end at ages 61, 51, and 41, respectively.

Table H-II lists the complete set of moments available for each cohort. Columns 2–4 show moments for the benchmark model cohorts (1945–1965), while columns 5–6 show those for the additional two cohorts used in the full model (1935, 1975).

Note that if we had complete data on a particular variable from age 17 to 65, then we would have 49 year-specific moments for that variable. But it is clear from Table H-II that we never have more than 44 moments for any one variable, and in most instances we have 41 or fewer. The main reasons for this are as follows:

First, at early ages, many people are still in school, and are not yet heads of households. As a result, moments for employment, wages, and marriage at ages 17–21 fluctuate substantially due to small sample sizes. Thus, we decided to only fit these moments from age 21 onward in estimation.

Second, only the 1945 and 1955 cohorts are actually observed through age 65. Furthermore, as we noted in Sections 3.6 and 5 of the text, we decided not to use the data from ages 62–65 in estimation, because we did not wish to model decisions to take up "early" Social Security retirement benefits at age 62.

This means that, in general, we attempt to use CPS data from ages 21 through 61 in estimation, meaning we have at most 41 periods of data and hence 41 moments.[16] Furthermore, the 1935 cohort is only observed from age 25 onward, reducing this figure to 37, the 1965 cohort is only observed through age 51, reducing this figure to 31, and the 1975 cohort is only observed through age 41, reducing this figure to 21.

Regarding the school distribution, we use data from 17 to 30 (assuming school is fixed from then onward), so we have at most 14 moments. And regarding children, we use data from 21 to 40, assuming no children are born to women over 40, giving at most 20 moments.

In total, there are 1505 moments for the 1945 and 1955 cohorts, and 1181 moments for the cohort of 1965. These three cohorts and 4191 moments are used to estimate the "baseline" model. In the "full" model we also include the 1281 moments for the 1935 cohort and the 861 moments for the 1975 cohort. This gives 6333 moments for the full model.

APPENDIX I: PARAMETER ESTIMATES

In Table I-I, we report the parameters that are present in the baseline model. These parameters are assumed fixed across all five cohorts. Table I-I reports the estimates ob-

[16]An exception is the health process, which we fit using IHIS data from 17 to 61, giving at most 45 moments. For the 1935 cohort, the health data are only available from age 27 to 61, giving 35 moments.

TABLE H-II

DATA MOMENTS USED IN ESTIMATION[a]

Moment	Benchmark Model Moments 1945[b]	1955[b]	1965[c]	Additional Moments 1935[b]	1975[d]
Full-time work: Married Women	41	41	31	37	21
Full-time work: Unmarried Women	41	41	31	37	21
Full-time work: Married Men	41	41	31	37	21
Full-time work: Unmarried Men	41	41	31	37	21
Part-time work: Married Women	41	41	31	37	21
Part-time work: Unmarried Women	41	41	31	37	21
Part-time work: Married Men	41	41	31	37	21
Part-time work: Unmarried Men	41	41	31	37	21
Married Women with Children	41	41	31	37	21
Married Women w/o Children	41	41	31	37	21
Unmarried Women with Children	41	41	31	37	21
Unmarried Women w/o Children	41	41	31	37	21
Men's Educ. distribution, 5 groups[e]	4×14	4×14	4×14	4×6	4×14
Women's Educ. distribution, 5 groups[e]	4×14	4×14	4×14	4×6	4×14
Marriage Rate	41	41	31	37	21
Divorce Rate	41	41	31	37	21
# of Kids: Married Women by Age[f]	20	20	20	16	20
# of Kids: Unmarried Women by Age[f]	20	20	20	16	20
Wage: Married Women	41	41	31	37	21
Wage: Unmarried Women	41	41	31	37	21
Wage: Married Men	41	41	31	37	21
Wage: Unmarried Men	41	41	31	37	21
Assortative Mating	5×5	5×5	5×5	5×5	5×5
Women's Wage by Educ. Level	5×41	5×41	5×31	5×37	5×21
Women's Emp. by Educ. Level	5×41	5×41	5×31	5×37	5×21
Women's Health distribution[g]	2×45	2×45	2×34	2×35	2×24
Men's Health distribution[g]	2×45	2×45	2×34	2×35	2×24

[a]Note: [b] Age 21 to 61 (for 1935: age 25–61), [c] age 21 to 51, [d] age 21 to 41, [e] schooling distribution from age 17 to 31, no schooling after 31 (for 1935 cohort, data start at age 25), [f] age 21 to 41 (no newborn after 41, for 1935 cohort data starts at age 25), [g] different source of data: IHIS (integrated health interview series) at Minnesota.

tained when we re-estimate these parameters in the "full specification" that also includes cohort varying labor market, marriage market, and fertility control parameters (these are reported in Tables I-II and I-III). Here, we highlight some of the more interesting estimation results:

The top panel of Table I-I reports the utility function estimates (equation (4)). The estimates of CRRA parameters for consumption and leisure are $\alpha = -0.477$ and $\gamma = 0.864$. In a static single agent model with a linear budget constraint and continuous hours, the Marshallian labor supply elasticity is simply $e_M = -\alpha/[(\alpha - 1) + (\gamma - 1)(h/l)]$. If we approximate $h = 0.5$ so $h/l = 1$, this gives $e_M = -0.30$. As $\alpha < 0$, utility is more concave than $\log(C)$, so the income effect dominates the substitution effect. Yet, given the full structure of our model, Marshallian elasticities are above 1.0 for married women and about 0.15 to 0.25 for other groups (see Table V in the text).

The second panel reports the AR(1) process for utility of leisure (equation (5)). As expected, it jumps up substantially for women with the arrival of a newborn ($\tau_{2f} = 1.39$), but this effect is much smaller for men ($\tau_{2m} = 0.29$). Interestingly, the AR(1) parameter is 0.969 for women but 0.676 for men. Thus, the arrival of a child has a much more persistent effect on tastes for leisure for women than for men.

TABLE I-I

UTILITY AND PREFERENCES PARAMETERS (ESTIMATED IN BENCHMARK MODEL)[a]

		Women		Men	
		Parameter	S.d.	Parameter	S.d.
Utility parameters (Eq. (4))					
Consumption CRRA parameter	α	−0.477	0.0668	”	
Leisure CRRA parameter	γ	0.864	0.0392	”	
Taste for leisure when pregnant	β^{0f}	0.0639	0.0049		
Taste for leisure by education	β^{I}	0.076	0.0100	0.000	0.0001
Taste for leisure by health	β^{2}	0.086	0.0042	0.049	0.0010
Utility from kids when married	A_j^M	0.713	0.0524	0.316	0.0260
Utility from kids when single	A_f^S	0.463	0.0418	0.073	0.0307
Utility from Leisure Equation (Eq. (5))					
Constant	τ_{0j}	0.002	0.0005	0.001	0.0008
AR(1) coefficient	τ_{1j}	0.969	0.0347	0.676	0.0384
Pregnancy in previous period	τ_{2j}	1.390	0.0421	0.286	0.0622
Marriage offer probability parameters					
Constant if below 18	p_0^H	−1.944	0.0629	”	
Constant if above 18 and in school	p_1^H	−1.548	0.0644	”	
Constant if above 18 and not in school	p_2^H	−1.360	0.0184	”	
Age	p_3^H	0.098	0.0089	0.104	0.0002
Age square	p_4^H	−0.002	0.0005	−0.002	0.0012
Taste for Marriage (Eq. (6))					
Constant	d_1	1.194	0.0990		
Schooling gap—men more educated	d_2	−2.096	0.0464		
Schooling gap—women more educated	d_3	−2.267	0.0917		
Health gap	d_4	−0.492	0.0760		
Utility from Pregnancy (Eq. (7))					
Married	π_1	0.328	0.0797		
Health	π_2	−0.088	0.0498		
# of kids in household	π_3	−0.953	0.0766		
Pregnency in $t-1$	π_4	−3.227	0.0618		
Utility from quality and quantity of children (Eq. (8))					
CES function parameter	ρ	−0.872	0.0454		
Wife leisure	a_f	0.527	0.0687		
Husband leisure	a_m	0.343	0.0950		
Spending per child	a_g	0.0004	0.0002		
Ability Distribution by Mother's education (Eq. (23))					
$P(low) = (1/3)[1 + I(PE \geq COL)\exp(e_1)]^{-1}$	e_1	0.870	0.0777	”	
$P(med) = (1/3) - P(low) + (1/3)[1 + I(PE \geq COL)\exp(e_2)]^{-1}$	e_2	0.239	0.0951	”	
Log standard deviations of shocks					
Permanent ability (skill endowment)		−0.564	0.0461	−0.598	0.0301
Taste for leisure		−1.425	0.0954	−1.313	0.0274
Transitory wage error		−0.618	0.0146	−0.625	0.0034
Match quality		−0.824	0.0809	”	
Taste for pregnancy		−0.234	0.0684	”	

(*Continues*)

TABLE I-I—*Continued*

		Women		Men	
		Parameter	S.d.	Parameter	S.d.
Utility from schooling (Eq. (17))					
Constant	ϑ_{0j}	0.464	0.0563	0.436	0.0338
Mother is CG	ϑ_{1j}	1.429	0.3289	0.554	0.3287
Labor market skill	ϑ_{2j}	0.659	0.0640	0.583	0.2139
Post high school tuition	TC	−1.411	0.0717	”	

[a]Standard errors of the estimated parameters are reported in the columns labelled S.d.. The symbol ” indicates that men and women share the same parameter value.

In the third panel of Table I-I, we see that, not surprisingly, marriage offer probabilities follow a quadratic in age (for both men and women). The estimates in the next panel, corresponding to equation (6), indicate that people are averse to marriages where the education or health of the partners is divergent.

The fifth panel reports estimates of equation (7), the tastes for pregnancy. As expected, there is a strong negative effect of pregnancy in the prior year. There is also a negative effect of children already present, a negative effect of health, and a positive effect of marriage.

The sixth panel reports estimates of the child quality production function. The woman's time is roughly 50% more productive than the man's. The monetary input has a significant positive effect.

The seventh panel of Table I-I reports how labor market skill depends on mother's education (Eq. (23)). The indicator for the mother being a college graduate has a strong positive effect on the probability her son/daughter is the high skill type. Finally, in the last panel of Table I-I, we see that mother's education has a large positive effect on a daughter's taste for school (Eq. (17)). This effect is three times greater than the effect for sons (1.429 vs. 0.554). The coefficient on labor market ability in (17) is positive for both women and men (0.659 and 0.583, respectively), indicating that labor market skill and taste for school are positively correlated.

Next, Table I-II reports the parameters of the offer wage function (22) and the job offer probability function (24). Recall that (24) determines the probabilities that unemployed workers receive part- and/or full-time offers. Workers who were employed in the previous period are assumed to be able to continue working, unless there is a forced separation. We discuss these estimates extensively in Section 6.1 of the main text, so we do not repeat that here.

The bottom panel of Table I-II reports the parameters of the logit model for exogenous job separation. (Note: This equation is mentioned but not written out in the main text.) The outcome is defined as 1 if a worker can keep their job and 0 if an exogenous separation occurs. The estimates imply that experience and education reduce the separation probability, while poor health increases it.

Finally, Table I-III reports the estimation of the marriage market matching process in equation (25), and the divorce cost parameters (equation (11)).

One notable result is that, for women, the intercept in the equation for probability of meeting a college graduate has risen across cohorts (from −0.644 in 1935 to 1.125 in 1975), but the negative shift in the intercept if the woman is only a HS graduate increased from −1.413 in 1935 to −2.110 in 1975. Thus, while the average probability of a woman meeting a college man has increased substantially, the reduction in this probability if she

TABLE I-II

LABOR MARKET PARAMETERS (ESTIMATED SEPARATELY FOR EACH COHORT BY FULL MODEL)[a]

		1935				1945				1955				1965				1975			
		Women		Men		Women		Men		Women		Men		Women		Men		Women		Men	
	Param.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.	Parameter	S.d.
Wage parameters (Eq. (22))																					
Experience:																					
HSD	ω^j_{2HSD}	0.020	0.0036	0.036	0.0051	0.029	0.0018	0.038	0.0010	0.022	0.0063	0.0289	0.0025	0.030	0.0023	0.044	0.0059	0.023	0.0010	0.046	0.0023
HSG	ω^j_{2HSG}	0.027	0.0056	0.039	0.0016	0.0276	0.0083	0.046	0.0037	0.033	0.0029	0.0456	0.0072	0.048	0.0060	0.072	0.0051	0.063	0.0077	0.073	0.0079
SC	ω^j_{2SC}	0.029	0.0089	0.049	0.0167	0.032	0.0008	0.058	0.0066	0.035	0.0024	0.060	0.0074	0.052	0.0035	0.077	0.0055	0.078	0.0075	0.082	0.0074
CG	ω^j_{2CG}	0.033	0.0029	0.052	0.0060	0.035	0.0046	0.063	0.0227	0.038	0.0085	0.064	0.0094	0.059	0.0040	0.085	0.0002	0.077	0.0042	0.086	0.0017
PC	ω^j_{2PC}	0.034	0.0069	0.061	0.0071	0.037	0.0085	0.073	0.0093	0.041	0.0032	0.074	0.0092	0.067	0.0012	0.096	0.0412	0.081	0.0067	0.095	0.0284
Experienced^2:																					
HSD	ω^j_{3HSD}	−0.0006	0.0001	−0.0006	0.0002	−0.0004	0.0001	−0.0006	0.0002	−0.0004	0.0001	−0.0005	0.0001	−0.0004	0.0002	−0.0008	0.0004	−0.0016	0.0001	−0.0011	0.0005
HSG	ω^j_{3HSG}	−0.0002	0.0001	−0.0007	0.0003	−0.0003	0.0001	−0.0008	0.0003	−0.0004	0.0001	−0.0008	0.0004	−0.0009	0.0004	−0.0013	0.0001	−0.0015	0.0006	−0.0018	0.0009
SC	ω^j_{3SC}	−0.0004	0.0001	−0.0008	0.0002	−0.0005	0.00004	−0.0010	0.0001	−0.0005	0.0001	−0.0011	0.0006	−0.0010	0.0005	−0.0015	0.0005	−0.0023	0.0006	−0.0022	0.0010
CG	ω^j_{3CG}	−0.0004	0.0001	−0.0008	0.0004	−0.0006	0.0001	−0.0012	0.0005	−0.0006	0.0001	−0.0010	0.0002	−0.0013	0.0002	−0.0018	0.0008	−0.0025	0.0007	−0.0024	0.0011
PC	ω^j_{3PC}	−0.0003	0.00004	−0.0009	0.0003	−0.0004	0.0001	−0.0012	0.0005	−0.0006	0.0001	−0.0012	0.0004	−0.0013	0.0006	−0.0022	0.0009	−0.0024	0.0008	−0.0027	0.0013
Intercept:																					
HSD	ω^j_{1HSD}	9.220	3.6185	9.522	0.2871	9.281	0.9745	9.638	0.0343	9.386	0.9919	9.771	0.5743	9.222	0.9835	9.487	0.3822	9.243	0.9746	9.332	0.0148
HSG	ω^j_{1HSG}	9.302	0.7990	9.715	0.8191	9.590	0.5012	9.930	0.8658	9.560	0.8492	9.920	0.7662	9.497	0.7801	9.533	0.8377	9.424	0.9494	9.556	0.0003
SC	ω^j_{1SC}	9.723	0.2804	9.957	0.8615	9.830	0.5422	9.980	0.6760	9.797	0.9306	9.990	0.3008	9.731	0.8235	9.750	0.9533	9.593	0.8637	9.710	0.0981
CG	ω^j_{1CG}	9.986	0.3486	10.113	0.7720	10.170	0.8540	10.220	0.7850	10.080	0.3957	10.150	0.8092	10.120	0.4533	10.110	0.6954	10.170	0.4894	10.180	0.0940
PC	ω^j_{1PC}	10.069	0.4754	10.134	0.5415	10.160	1.9201	10.180	0.9898	10.380	0.8860	10.280	0.1354	10.190	0.7127	10.310	0.8953	10.410	0.8603	10.430	0.0699

(*Continues*)

TABLE I-II—*Continued*

		1935				1945				1955				1965				1975			
		Women		Men		Women		Men		Women		Men		Women		Men		Women		Men	
	Param.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.
Job offer parameters (Eq. (24))																					
Full Time:																					
Constant	ϕ_{j01}	−0.718	0.0563	−0.277	0.0430	−0.647	0.0380	−0.293	0.0411	−0.601	0.0865	−0.293	0.0386	−0.573	0.0290	−0.316	0.0939	−0.563	0.0649	−0.372	0.0973
Experience	ϕ_{j21}	0.090	0.0053	0.167	0.0182	0.103	0.0075	0.173	0.0423	0.106	0.0071	0.175	0.0546	0.122	0.0079	0.163	0.0451	0.125	0.0052	0.169	0.0125
Education	ϕ_{j11}	0.039	0.0029	0.072	0.0090	0.056	0.0066	0.075	0.0094	0.086	0.0376	0.088	0.0101	0.105	0.0316	0.103	0.0351	0.113	0.0247	0.120	0.0346
Health	ϕ_{j31}	−0.388	0.0989	−0.432	0.0435	−0.412	0.0944	−0.419	0.0535	−0.430	0.0541	−0.406	0.0939	−0.455	0.0781	−0.417	0.0859	−0.497	0.0414	−0.430	0.0638
Part Time:																					
Constant	ϕ_{j02}	−0.682	0.0785	0.002	0.0005	−0.659	0.0895	0.001	0.0007	−0.568	0.0979	0.001	0.0003	−0.587	0.0390	0.001	0.0007	−0.597	0.0366	0.001	0.0002
Experience	ϕ_{j22}	0.098	0.0451	0.055	0.0083	0.099	0.0233	0.059	0.0088	0.108	0.0572	0.060	0.0059	0.115	0.0236	0.062	0.0076	0.102	0.0336	0.064	0.0057
Education	ϕ_{j12}	0.044	0.0091	0.007	0.0015	0.055	0.0098	0.007	0.0009	0.064	0.0022	0.007	0.0033	0.061	0.0076	0.007	0.0038	0.062	0.0306	0.007	0.0034
Health	ϕ_{j32}	−0.398	0.0627	−0.411	0.0417	−0.422	0.0473	−0.423	0.0545	−0.417	0.0428	−0.411	0.0315	−0.496	0.0846	−0.543	0.0383	−0.556	0.0455	−0.663	0.0560
No Job Separation (Probability)																					
Constant		1.411	0.0717	1.331	0.6101	1.436	0.1028	1.264	0.4846	1.429	0.0816	1.290	0.3291	1.403	0.1226	1.317	0.1955	1.425	0.2681	1.286	0.2312
Experience		0.202	0.0768	0.277	0.0286	0.203	0.0896	0.284	0.0261	0.194	0.0718	0.266	0.0887	0.196	0.0470	0.277	0.0307	0.208	0.0962	0.240	0.0303
Education		0.114	0.0211	0.084	0.0044	0.107	0.0409	0.088	0.0267	0.120	0.0467	0.093	0.0359	0.109	0.0554	0.098	0.0106	0.113	0.0366	0.097	0.0276
Health		−0.402	0.0285	−0.488	0.0290	−0.434	0.0569	−0.427	0.0208	−0.428	0.0827	−0.421	0.0149	−0.839	0.0525	−0.633	0.0775	−1.020	0.0977	−0.880	0.0096

[a]Standard errors of the estimated parameters are reported in the columns labelled S.d..

TABLE I-III

MARRIAGE MARKET PARAMETERS (ESTIMATED SEPARATELY FOR EACH COHORT)[a]

		1935				1945				1955				1965				1975			
		Women		Men		Women		Men		Women		Men		Women		Men		Women		Men	
	Param.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.	Param-eter	S.d.
Marriage offer probability parameters (Eq. (25))																					
Probability of meeting a CG:																					
Constant	η_{0j}^{C}	−0.644	0.0620	−0.254	0.0568	−0.390	0.0526	0.016	0.0039	0.175	0.0298	0.225	0.0258	0.731	0.0843	0.590	0.0657	1.125	0.0189	0.711	0.0151
Educ = SC	η_{2j}^{C}	−0.191	0.0549	−1.234	0.0843	−0.232	0.0276	−1.163	0.0183	−0.604	0.0121	−1.099	0.0810	−1.180	0.0728	−1.140	0.0697	−1.377	0.0635	−1.170	0.0978
Educ = HS	η_{1j}^{C}	−1.413	0.0390	−2.394	0.0630	−1.610	0.0267	−2.240	0.0776	−1.870	0.0042	−1.855	0.0660	−1.900	0.0393	−1.690	0.0817	−2.110	0.0979	−1.788	0.0250
Probability of meeting a SC:																					
Constant	η_{0j}^{SC}	−0.635	0.0605	−0.293	0.0993	−0.564	0.0554	−0.255	0.0735	−0.469	0.0219	−0.189	0.0242	−0.317	0.0710	−0.114	0.0063	−0.155	0.0876	−0.050	0.0057
Educ = HS	η_{1j}^{SC}	−0.392	0.0301	−1.363	0.0940	−0.277	0.0516	−1.250	0.0671	−0.191	0.0939	−0.932	0.0277	−0.120	0.0261	−0.690	0.0705	−0.133	0.0394	−0.640	0.0771
Divorce Cost (Eq. (11))																					
Fixed cost	α_4^j	−2.855	0.9451	−1.296	0.0731	−2.144	0.1040	−1.422	0.0808	−1.800	0.7403	−1.534	0.6193	−1.471	0.0951	−1.624	0.0923	−1.570	0.0761	−1.688	0.0889
Cost per child	α_5^j	−0.383	0.0885	−0.276	0.0584	−0.377	0.0558	−0.260	0.0535	−0.372	0.0187	−0.266	0.0290	−0.353	0.0485	−0.244	0.0337	−0.356	0.0873	−0.259	0.0659

[a] Meeting a HS type is the omitted category in the MNL model. Standard errors of the estimated parameters are reported in the columns labelled S.d..

herself is not a college graduate has also increased substantially. Thus, the returns to education in the marriage market matching process for women have increased.

The constant in the fixed cost of divorce equation drops sharply for women from −2.855 in the 1935 cohort to −1.800 in the 1955 cohort. After that, it stabilizes and drops only slightly more to −1.570 in the 1975 cohort. For men, in contrast, the constant fixed cost of divorce rose slightly from the 1935 to 1975 cohorts, from −1.296 to −1.688. The coefficient on children has remained stable across cohorts at about −0.36 for women and about −0.25 for men. So, in the 1935 to 1945 cohorts, the cost of divorce was much greater for women than for men, but in later cohorts, divorce costs have roughly equalized.

APPENDIX J: FIT OF THE MODEL

Here we present the fit of both the "benchmark" and "full" specifications to mean wages and employment rates by cohort, broken down by gender, marital status, and age.

In Table J-I, we use shading to highlight aspects of the data that the models fit poorly. These are not formal tests of fit, but merely a visual aid to help the reader see where the fit appears to be poor. We define fitting "poorly" as cases where the fitted values are more than 5 percent different from the data. Obviously, the benchmark model fits poorly for all cohorts except 1955. In particular, the estimated wages from the benchmark fit the data poorly for all other cohorts for all gender/marriage/age cells. The benchmark model fits the employment data for men rather well in all cohorts. But it provides a very poor fit to employment data for women. In particular, it greatly over-predicts wages/employment for married women in the 1935–1945 cohorts, and under-predicts these quantities for the 1965–1975 cohorts. However, Table J-I also indicates that the "full specification" provides a very good fit to essentially all moments involving wages and employment for all gender, marital status, and age cells.

Table J-II presents the fit of both the "benchmark" and "full" specifications to marriage and divorce rates, assortative mating, fertility, and education. Observe that the shaded cells highlight that the benchmark model fits poorly for all cohorts except 1955 (and to a lesser extent, 1965). In particular, it greatly or moderately understates or overstates the demographic outcomes for the 1935, 1945, and 1975 cohorts (in the directions one would expect intuitively).

On the other hand, Table J-II indicates that the full model matches *all key* moments involving marriage/divorce rates, assortative mating, fertility, and education for all five cohorts quite accurately. This establishes the result that adding only the three exogenous factors we consider (i.e., marriage market factors, labor market factors and contraception) is *sufficient* in that the full specification provides a good fit to all endogenous variables in nearly all gender/marital-status/age cells.

J.1. *Untargeted Moments—Transition Matrix for Employment and Marriage/Divorce*

The CPS is a cross-section survey, so we did not fit our model to transition rates. However, as an out-of-sample validity test, we calculated employment and marriage transition rates for women from the NLSY panel. The NLSY contains individuals born from 1957 to 1965 (ages 14–22 at 1979). We restricted the NLSY sample to individuals born 1963–1965, to make it as similar as possible to the 1965 cohort in our model. We then constructed the annual transition rates between employment states, conditional on marital status and education (giving 20 untargeted moments). We also constructed the annual transition rates between marriage and divorce, conditional on education (giving 10 untargeted moments).

TABLE J-I

MODEL FIT TO WAGES AND EMPLOYMENT[a]

	1935 (Out of Sample)			1945			1955			1965			1975 (Out of Sample)		
		Predicted			Predicted			Predicted			Predicted			Predicted	
		Specification			Specification			Specification			Specification			Specification	
	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full
Gross Wages (Thousands of $)															
Married Women—Ages 25–34	20.4	28.15	20.5	25.3	27.98	26.9	28.8	28.99	29.6	32.7	30.64	33.5	40.1	31.22	39.0
Married Women—Ages 35–44	24.4	35.63	25.1	29.9	35.80	31.1	36.8	36.27	37.7	44.8	38.56	45.2	49.3	37.68	51.1
Married Women—Ages 45–54	28.0	42.59	28.6	36.6	42.78	37.9	45.9	43.40	44.4	47.5	44.85	49.0	No Data		
Unmarried Women—Ages 25–34	22.4	29.71	23.3	27.4	29.28	27.2	30.5	29.62	30.2	33.1	29.77	33.6	38.0	29.60	37.7
Unmarried Women—Ages 35–44	27.9	38.17	28.4	33.0	38.11	33.2	38.3	38.01	38.4	42.4	38.41	44.4	44.0	37.17	43.6
Unmarried Women—Ages 45–54	31.7	44.11	32.6	38.1	44.24	39.5	45.5	44.35	47.1	47.5	44.18	50.7	No Data		
Married Men—Ages 25–34	35.6	42.18	36.2	42.3	42.28	41.9	42.8	42.56	43.3	43.5	43.02	43.5	50.4	44.57	51.3
Married Men—Ages 35–44	50.8	60.00	52.2	57.1	60.03	57.2	59.4	60.50	60.3	70.9	60.94	71.8	67.8	60.94	69.4
Married Men—Ages 45–54	58.0	72.42	59.3	64.1	72.55	66.2	76.0	73.72	76.6	77.8	73.22	79.9	No Data		
Unmarried Men—Ages 25–34	30.8	35.74	30.0	36.6	35.98	37.8	37.2	36.40	37.8	37.9	36.65	37.3	41.5	36.41	42.9
Unmarried Men—Ages 35–44	40.2	47.56	42.9	48.4	47.42	49.3	44.9	47.25	46.5	49.6	47.56	51.7	53.5	46.64	55.1
Unmarried Men—Ages 45–54	49.8	54.23	52.3	53.1	54.52	54.7	54.2	54.37	55.2	54.3	53.94	56.5	No Data		
Employment															
Married Women—Ages 25–34	0.26	0.54	0.27	0.38	0.54	0.39	0.55	0.54	0.55	0.62	0.55	0.60	0.61	0.57	0.63
Married Women—Ages 35–44	0.45	0.64	0.44	0.59	0.64	0.56	0.67	0.64	0.65	0.65	0.64	0.66	0.64	0.62	0.65
Married Women—Ages 45–54	0.53	0.70	0.53	0.66	0.70	0.67	0.70	0.70	0.70	0.67	0.71	0.70	No Data		
Unmarried Women—Ages 25–34	0.68	0.72	0.68	0.72	0.72	0.71	0.75	0.71	0.74	0.74	0.72	0.75	0.74	0.74	0.75
Unmarried Women—Ages 35–44	0.68	0.75	0.70	0.74	0.75	0.75	0.76	0.74	0.77	0.74	0.75	0.76	0.69	0.76	0.72
Unmarried Women—Ages 45–54	0.68	0.73	0.70	0.74	0.73	0.74	0.72	0.74	0.76	0.68	0.74	0.73	No Data		
Married Men—Ages 25–34	0.93	0.92	0.91	0.91	0.92	0.91	0.88	0.91	0.88	0.89	0.91	0.88	0.89	0.92	0.89
Married Men—Ages 35–44	0.91	0.93	0.92	0.89	0.93	0.90	0.90	0.92	0.90	0.90	0.92	0.90	0.88	0.92	0.90
Married Men—Ages 45–54	0.85	0.89	0.87	0.86	0.89	0.87	0.86	0.89	0.86	0.85	0.89	0.87	No Data		
Unmarried Men—Ages 25–34	0.83	0.77	0.78	0.79	0.77	0.76	0.78	0.78	0.75	0.81	0.77	0.78	0.80	0.79	0.79
Unmarried Men—Ages 35–44	0.80	0.79	0.79	0.80	0.79	0.79	0.77	0.80	0.78	0.76	0.79	0.78	0.74	0.82	0.75
Unmarried Men—Ages 45–54	0.70	0.73	0.72	0.72	0.73	0.71	0.71	0.72	0.72	0.69	0.72	0.72	No Data		

[a]The shaded cells indicate that the fitted value differs from the data value buy at least 5 percent. Gross Wage Data: Real Annual Wages of Full-Time Full-Year Caucasian workers (2012 Prices). Employment Data: The fraction employed out of total Caucasian population. We define "employment" as working at least 10 hours a week. For cohort 65, data are available until age 51. For cohort 75, data are available until age 41.

TABLE J-II

MODEL FIT TO FAMILY MOMENTS AND EDUCATION[a]

	1935 (Out of Sample)			1945			1955			1965			1975 (Out of Sample)		
		Predicted			Predicted			Predicted			Predicted			Predicted	
		Specification			Specification			Specification			Specification			Specification	
	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full
Family moments															
Marriage Rate—Ages 25–34	0.87	0.74	0.86	0.81	0.74	0.82	0.70	0.70	0.72	0.64	0.65	0.65	0.61	0.61	0.60
Marriage Rate—Ages 35–44	0.84	0.73	0.84	0.77	0.74	0.77	0.73	0.73	0.73	0.71	0.72	0.71	0.69	0.70	0.70
Divorce Rate—Ages 25–34	0.03	0.09	0.03	0.07	0.09	0.07	0.10	0.09	0.10	0.09	0.09	0.10	0.07	0.09	0.09
Divorce Rate—Ages 35–44	0.07	0.14	0.08	0.13	0.14	0.13	0.14	0.14	0.15	0.14	0.15	0.15	0.12	0.15	0.12
Married Women # of Children—Ages 25–34	2.73	1.60	2.69	1.95	1.60	1.87	1.53	1.56	1.58	1.48	1.52	1.47	1.49	1.47	1.51
Married Women # of Children—Ages 35–44	2.29	1.87	2.24	1.96	1.87	2.03	1.80	1.87	1.89	1.87	1.86	1.85	1.94	1.94	1.97
UnMarried Women # of Children—Ages 25–34	0.97	0.36	0.92	0.43	0.37	0.46	0.34	0.35	0.33	0.35	0.31	0.30	0.36	0.29	0.32
UnMarried Women # of Children—Ages 35–44	0.67	0.53	0.75	0.55	0.53	0.58	0.49	0.53	0.51	0.50	0.52	0.51	0.53	0.51	0.50
Women education distribution at 30															
HSD	0.29	0.16	0.28	0.19	0.16	0.19	0.12	0.12	0.12	0.11	0.11	0.10	0.12	0.11	0.10
HSG	0.49	0.42	0.50	0.45	0.42	0.46	0.39	0.40	0.40	0.34	0.38	0.33	0.26	0.30	0.25
SC	0.14	0.23	0.17	0.18	0.23	0.19	0.26	0.25	0.25	0.30	0.28	0.33	0.28	0.31	0.29
CG	0.08	0.16	0.05	0.15	0.16	0.14	0.19	0.19	0.19	0.20	0.19	0.19	0.24	0.21	0.25
PC	0.01	0.03	0.00	0.03	0.03	0.02	0.05	0.04	0.04	0.05	0.04	0.05	0.10	0.07	0.11
Men education distribution at 30															
HSD	0.29	0.15	0.28	0.18	0.15	0.19	0.12	0.14	0.13	0.14	0.14	0.13	0.16	0.14	0.14
HSG	0.35	0.35	0.36	0.34	0.35	0.35	0.36	0.35	0.35	0.34	0.35	0.33	0.31	0.33	0.31
SC	0.16	0.23	0.16	0.22	0.23	0.21	0.24	0.24	0.24	0.27	0.25	0.28	0.25	0.26	0.26
CG	0.15	0.19	0.15	0.17	0.19	0.16	0.20	0.19	0.20	0.19	0.18	0.20	0.20	0.19	0.21
PC	0.06	0.08	0.05	0.09	0.08	0.09	0.08	0.08	0.08	0.06	0.08	0.06	0.07	0.08	0.08

(*Continues*)

TABLE J-II—*Continued*

	1935 (Out of Sample)			1945			1955			1965			1975 (Out of Sample)		
		Predicted Specification			Predicted Specification			Predicted Specification			Predicted Specification			Predicted Specification	
	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full	Data	Benchmark	Full
Assortative Mating															
HSD with HSD	0.59	0.55	0.55	0.55	0.55	0.54	0.51	0.53	0.55	0.52	0.54	0.55	0.58	0.55	0.56
HSG with HSG	0.67	0.57	0.64	0.67	0.57	0.69	0.63	0.59	0.59	0.53	0.57	0.51	0.46	0.55	0.49
SC with SC	0.25	0.39	0.24	0.34	0.39	0.32	0.43	0.39	0.41	0.48	0.41	0.50	0.49	0.41	0.53
CG with CG	0.30	0.38	0.33	0.38	0.38	0.40	0.41	0.40	0.43	0.48	0.44	0.51	0.51	0.43	0.49
PC with PC	0.10	0.29	0.12	0.22	0.29	0.25	0.30	0.32	0.32	0.33	0.32	0.36	0.45	0.37	0.43
HSG Women with CG Men	0.35	0.21	0.34	0.24	0.21	0.22	0.18	0.17	0.16	0.12	0.17	0.09	0.07	0.18	0.08
CG Women with HSG Men	0.02	0.09	0.02	0.04	0.09	0.03	0.07	0.09	0.08	0.10	0.09	0.11	0.13	0.09	0.12

[a]The shaded cells indicate that the fitted value differs from the data value by at least 10 percent. HSD—High school dropout. HSG—High school graduate. SC—Some college. CG—College graduate. PC—Post college. For cohort 65, data are available until age 51. For cohort 75, data are available until age 41.

TABLE J-III

FIT TO UNTARGETED MOMENTS

	HSD		HSG		SC		CG		PC	
	NLSY	Model	NLSY	Model	NLSY	Model	NLSY	Model	NLSY	Model
Married Women:										
Employment to Employment	0.84	0.89	0.86	0.88	0.88	0.91	0.90	0.94	0.90	0.93
Unemployment to Employment	0.24	0.33	0.24	0.32	0.23	0.30	0.22	0.33	0.26	0.32
Unmarried Women:										
Employment to Employment	0.90	0.93	0.91	0.92	0.92	0.94	0.96	0.97	0.97	0.96
Unemployment to Employment	0.36	0.38	0.35	0.40	0.46	0.49	0.68	0.73	0.59	0.69
Married to Divorced	0.06	0.08	0.06	0.08	0.04	0.07	0.02	0.05	0.04	0.05
Single/Divorced to Married	0.15	0.22	0.15	0.22	0.16	0.22	0.16	0.24	0.15	0.23

Table J-III compares the transition rates in the NLSY with those predicted by our full model.

As can be seen from Table J-III, the fit to the transition rates between employment states is remarkably good, considering these moments were untargeted. The transition rate from unemployment to employment is sharply increasing with education for single women (in both the data and the model). But interestingly, for married women, the transition rate from unemployed to employed is low regardless of education level. The model captures this rather subtle difference very well.

The transition rate from married to divorced is slightly lower in the NLSY than is predicted by our model. But the model does capture that the divorce rate falls with education. The transition rate from single to married is about 15% to 16% in the NLSY data for all education groups, while our model gets the figure a bit too high (i.e., 22% to 24%). But our model does capture that the marriage rate hardly varies with education.

APPENDIX K: DECOMPOSING SOURCES OF COHORT DIFFERENCES, ALTERNATIVE METHOD

Here we report effects of changing the factors one at time holding other factors fixed.

It is notable that the differences between Tables I and III in the text and Tables K-I and K-II here are minor, and that in all cases, the individual factor contributions add up to roughly 100% of the total change predicted by the full model. Thus, "step-by-step" and "one-at-time" approaches to assessing the contribution of each factor give almost identical results.

An earlier working paper version of this article, Eckstein et al. (2016), discussed in some detail the intermediate models obtained by adding factors (ii), (iii) and (iv) in that order.

APPENDIX L: ROBUSTNESS CHECKS: HOME PRODUCTION AND SAVINGS

In this appendix, we explore extensions of the model to include home production and a simple form of buffer stock savings.

L.1. *Accounting for Home Production*

Greenwood et al. (2016) argued that changes in the cost of household production may provide an alternative explanation—aside from changes in availability of contraception—

TABLE K-I

"ONE AT A TIME" CONTRIBUTIONS OF EACH FACTOR—WAGES AND EMPLOYMENT

	1935 Fitted	1975 Fitted	Total % Change	Contribution of Each Factor: Benchmark	Marriage Market	Labor Market	Contraception
Wages (Thousands of $)							
Married Women—Ages 25–34	20.5	39.0	90%	11%	7%	68%	4%
Married Women—Ages 35–44	25.1	51.2	104%	12%	2%	80%	3%
Unmarried Women—Ages 25–34	23.3	37.7	62%	4%	5%	54%	2%
Unmarried Women—Ages 35–44	28.4	43.5	53%	3%	3%	50%	1%
Married Men—Ages 25–34	36.2	51.3	42%	1%	1%	40%	0%
Married Men—Ages 35–44	52.2	69.8	34%	1%	1%	32%	0%
Unmarried Men—Ages 25–34	30.0	42.9	43%	3%	1%	39%	0%
Unmarried Men—Ages 35–44	42.9	56.3	31%	2%	1%	27%	0%
Employment							
Married Women—Ages 25–34	0.27	0.63	130%	13%	30%	82%	34%
Married Women—Ages 35–44	0.44	0.66	50%	4%	11%	41%	7%
Unmarried Women—Ages 25–34	0.68	0.75	11%	1%	0%	8%	2%
Unmarried Women—Ages 35–44	0.70	0.72	2%	0%	0%	2%	0%
Married Men—Ages 25–34	0.91	0.89	−2%	0%	−1%	−1%	0%
Married Men—Ages 35–44	0.92	0.90	−2%	0%	−1%	−2%	0%
Unmarried Men—Ages 25–34	0.78	0.79	2%	0%	0%	2%	0%
Unmarried Men—Ages 35–44	0.79	0.75	−5%	0%	0%	−5%	0%

TABLE K-II

"ONE AT A TIME" CONTRIBUTION OF EACH FACTOR: MARRIAGE, CHILDREN, AND EDUCATION

	1935 Fitted	1975 Fitted	Total % Change	Contribution of Each Factor: Benchmark	Marriage Market	Labor Market	Contraception
Family moments							
Marriage Rate—Ages 25–34	0.86	0.60	−30%	−20%	−7%	−3%	−1%
Marriage Rate—Ages 35–44	0.84	0.70	−16%	−8%	−6%	−2%	−1%
Divorce Rate—Ages 25–34	0.03	0.09	206%	32%	136%	11%	18%
Divorce Rate—Ages 35–44	0.08	0.12	62%	2%	52%	7%	3%
Married Women # of Children—Ages 25–34	2.54	1.51	−41%	−8%	−13%	−2%	−22%
Married Women # of Children—Ages 35–44	2.24	1.94	−14%	−2%	−5%	0%	−7%
UnMarried Women # of Children—Ages 25–34	0.92	0.32	−66%	−6%	−6%	−3%	−54%
UnMarried Women # of Children—Ages 35–44	0.75	0.51	−32%	−3%	−2%	−1%	−25%
Education distribution at 30							
Women's CG + PC rate	0.05	0.36	620%	180%	180%	160%	60%
Men's CG + PC rate	0.20	0.29	45%	5%	10%	25%	0%
Assortative Mating							
HSD with HSD	0.55	0.56	2%	0%	2%	2%	0%
HSG with HSG	0.64	0.49	−23%	−9%	−8%	−6%	−2%
SC with SC	0.24	0.53	121%	−4%	21%	83%	4%
CG with CG	0.33	0.49	48%	6%	15%	30%	0%
PC with PC	0.12	0.43	258%	33%	50%	175%	8%
HSG Women with CG Men	0.34	0.08	−76%	−9%	−24%	−56%	0%
CG Women with HSG Men	0.02	0.12	500%	100%	150%	250%	0%

for the high fertility and low employment of young married women in the 1935–1945 cohorts. We explored this issue in several ways.

First, we worked with a version of our benchmark model that added factor (ii) marriage market conditions and (iii) labor market conditions, but that excluded factor (iv) contraception. We found that this model generated too little fertility and too much employment for young women in the 1935 and 1945 cohorts (see the working paper Eckstein et al. (2016) for more details).[17] Then we tried to add home production to this model in two ways:

First, following Greenwood et al. (2016), we tried to increase the cost of children for the early cohorts. Specifically, we increased the parameter α_f in (8), so women's time with children is more valuable. This closed the gap in employment but it did not increase the number of children. Second, we changed the parameters of equation (4), the home time equation, specifically τ_{2j} and τ_{1j}, so as to decrease employment, but this also did not increase the number of children.[18] We take these results to mean that home production cannot *replace* contraception as an explanation for the observed data patterns.

Next, we asked whether adding home production time to our full specification would improve its fit and/or change its decompositions of which factors drove which behavioral changes. To do this, we modified the time budget to $h_t^j + l_t^j + pd_t^j = 1$ where we interpret pd as an exogenously given quantity of time that is required for home production during each period (e.g., cleaning, laundry). A higher value of pd means a person has less leisure for any given level of work, thus discouraging work. We normalized $pd = 0$ for each individual in the 1975 cohort, and then estimated its value in earlier cohorts. As expected, we obtain $pd > 0$ for earlier cohorts (particularly 1935), but the values were too small to have any noticeable effect on the behavior of our model.

Thus, we conclude that adding home production does not improve the fit of our model, or substantively alter its predictions. But we do not view this result as necessarily contradicting the argument in Greenwood et al. (2016) for the importance of home production technology in explaining changes in employment and fertility over time. This is because most of the improvements in home production technology that they emphasized had already occurred by 1950. Thus, they may well have had large effects on earlier cohorts.[19]

L.2. *Including Buffer Stock Savings*

Second, it is possible that incorporating savings might lead to significant changes in the behavior of our model. Unfortunately, a practical point is that the addition of saving as an additional state variable, and consumption as an additional choice, would render solution of the model—which already resides on the computers' production possibility frontier—essentially impossible.[20]

Furthermore, given results in Keane and Wolpin (2001), we are doubtful that including savings would have a first-order impact on the major life-cycle decisions that we focus on,

[17]The model without contraception exaggerates the ability of women in the early cohorts to control fertility.

[18]Eckstein and Lifshitz (2011) found these parameters can account for 30% of the female employment change when fertility is taken as exogenous. But with endogenous fertility we find that this result no longer holds.

[19]The 1925 and earlier cohorts would have been more influenced by the introduction of technologies like washing machines, refrigerators, disposable diapers, etc.

[20]To give a sense of the magnitude of the problem, even in our current model, for a single person at age 30 the state space has 43,200 points, while for a married person it has roughly 700 million points.

such as education, marriage, employment, and fertility.[21] Rather, we suspect (supported by some evidence we report below) that the main impact of including savings would be to alter individuals' responses to transitory shocks, which is not a focus of our work (which aims to explain more long-term decisions).

To check this conjecture, we decided to introduce a simple form of consumption smoothing into our model to test if it would affect our results. We assume that in each period, an individual (or household) has a choice whether to create a buffer stock of saving. To make the model computationally feasible, we assume the buffer stock can only take on one value B, so that the state space for saving has only two points, $S \in \{0, B\}$. A consumer (or household) in state $S = 0$ at the start of a period has two options: either stay at $S = 0$ or accumulate a buffer stock and move to $S = B$. A consumer (or household) in state $S = B$ at the start of a period has two options: either stay at $S = B$ or spend the buffer stock and move to $S = 0$. Although very simple, this setup does generate the key mechanism that a consumer (or household) can choose to accumulate a buffer stock in a "good" year and then save it to smooth consumption in a "bad" year. It has the virtue that it only doubles the state space, and only adds one discrete choice.[22]

We experimented with several values of B, but we focus on results with $B = \$4500$. This corresponds to roughly 5% of the annual income of a married couple, and about 10% of the annual income of a typical single person. We then added this feature to our "full" specification and iterated until convergence using the data for the 1965 cohort. We found no evidence of any improvement in model fit, or any significant changes in the estimated parameters.

Finally, we used the two versions of the model (with and without savings) to calculate Marshallian and "Frisch" elasticities. Specifically, we calculated Marshallian elasticities by simulating permanent 5% wage increases for both genders (for the whole life). We calculated "Frisch" elasticities by simulating a transitory wage increase of 5% that occurs at age 30, 40, or 50. The results are reported in Table L-I.[23]

As expected, when we simulate responses to transitory wage changes, they are slightly larger in the model with savings than in our "full" specification, but they continue to be very small. For example, for married women, elasticities at ages 30, 40, and 50 increase from $(0.06, 0.08, 0.08)$ to $(0.10, 0.11, 0.13)$, respectively. We experimented with several other values of B and found the same basic results. Thus, at least at the margin, extending the model to allow for modest amounts of saving has very little impact on the results.

However, Marshallian elasticities with respect to permanent wage changes were essentially unchanged when we introduce savings (see Table L-I, right panel). Thus, as we expected a priori, extending the model to allow for modest amounts of saving leads to small

[21]Keane and Wolpin (2001) introduced savings into the model of Keane and Wolpin (1997), and found that it had a negligible impact on school and labor supply decisions. Its primary impact was to increase the amount that students consumed while in school. On the other hand, the paper by Borella et al. (2017), which we discussed in Section 7, has a key focus on the effect of spousal Social Security benefits on retirement behavior. They sensibly modeled savings, as it is presumably a first-order issue for retirement. They found that elimination of spousal benefits would substantially increase labor supply of married women.

[22]Notably, life-cycle models of saving in the literature typically generalize this framework simply by assuming that B lies on a grid of several discrete values, and, in practice, small numbers of grid points are often used for the sake of computational tractability. See, for example, Buchinsky, M. and A. Mezza (2018), "Illegal Drugs, Education and Labor Market Outcomes," where assets have four discrete levels.

[23]We are using the terminology "Frisch" elasticity rather loosely here to refer to responses to transitory wage changes in general. Technically, however, the Frisch elasticity is not defined in the model with no savings, as the very concept presupposes that one can smooth consumption across periods so as to stabilize the marginal utility of consumption.

TABLE L-I

THE INFLUENCE OF SAVINGS ON LABOR SUPPLY ELASTICITIES[a]

Elasticities With Respect to Transitory Wage Shocks			Marshallian Elasticities With Respect to Permanent Wage Changes		
Frisch Elasticities—Cohort of 1965	No Saving	With Saving	Marshallian Elasticities—Cohort of 1965	No Saving	With Saving
Married Women—Ages 30	0.06	0.10	Married Women—Ages 25–34	1.25	1.23
Married Women—Ages 40	0.08	0.11	Married Women—Ages 35–44	1.12	1.10
Married Women—Ages 50	0.08	0.13	Married Women—Ages 45–54	1.06	1.07
Unmarried Women—Ages 30	0.04	0.03	Unmarried Women—Ages 25–34	0.18	0.22
Unmarried Women—Ages 40	0.03	0.04	Unmarried Women—Ages 35–44	0.21	0.25
Unmarried Women—Ages 50	0.05	0.06	Unmarried Women—Ages 45–54	0.20	0.22
Married Men—Ages 30	0.01	0.02	Married Men—Ages 25–34	0.17	0.17
Married Men—Ages 40	0.04	0.04	Married Men—Ages 35–44	0.15	0.15
Married Men—Ages 50	0.02	0.02	Married Men—Ages 45–54	0.15	0.16
Unmarried Men—Ages 30	0.02	0.02	Unmarried Men—Ages 25–34	0.18	0.16
Unmarried Men—Ages 40	0.01	0.02	Unmarried Men—Ages 35–44	0.16	0.20
Unmarried Men—Ages 50	0.02	0.03	Unmarried Men—Ages 45–54	0.22	0.20

[a]Frisch elasticities for a 5% transitory wage increase at a specific age. We report three experiments where the wage shock occurs at age 30, 40, or 50. We calculated the Marshallian elasticities by simulating permanent 5% wage increases for people of both genders (for the whole life).

increases in responses to transitory wage changes, but has almost no effect on Marshallian elasticities with respect to permanent wage changes. This is encouraging given that we focus on using our model to (i) examine effects of permanent changes in the wage structure (Section 6.1) and (ii) predict responses to *permanent* changes in tax rules (Section 7).

A final interesting point is that, contrary to conventional wisdom, Marshallian elasticities with respect to permanent wage changes exceed the elasticities with respect to transitory wage changes. Keane (2016) showed how this may occur in a standard life-cycle labor supply model with human capital and borrowing constraints, as a permanent wage change has a larger effect on the shadow price of time.[24]

Co-editor Liran Einav handled this manuscript.

Manuscript received 14 June, 2016; final version accepted 20 July, 2018; available online 8 August, 2018.

[24]See Keane, Michael (2016), Life-Cycle Labour Supply with Human Capital: Econometric and Behavioural Implications, *The Economic Journal*, 126(592), 546–577.