Sources of Change in the Life-Cycle Decisions of American Men and Women: 1962-2014

by

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Abstract: We study life-cycle decisions of five cohorts of American men and women born from the 1930s to the 1970s in a unified econometric framework applied to CPS data. The men and women in our model make individual decisions when single, joint decisions when married, and interact in a marriage market. Our model succeeds in explaining differences across cohorts in several key endogenous variables (i.e., education, work, marriage/divorce and fertility). We explain these changes using shifts in five exogenous factors: parental education, the distribution of potential partners, divorce laws, the wage/job offer distribution, and birth control technology. A major change between the 1935 and 1975 cohorts is that the female "marriage wage premium" rose from -10% to +7%. We find that changes in the selection of women into marriage explain 75% of this change. Married women of recent cohorts have much higher observed and unobserved skills compared both to unmarried women and the married women of past cohorts.

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I. Introduction

In this paper we study the life-cycle decisions of five cohorts of American men and women born from the 1930s to the 1970s using the CPS data from 1962 to 2014. We extend the literature by modelling the joint endogenous life-cycle decisions on education, work, marriage/divorce and children – all of which differ in major ways across the five cohorts, especially for women. We explain the changes across cohorts by shifts in five exogenous sources: parental education, the opportunities in the marriage market, divorce laws (costs of divorce), the wage offer distribution, and birth control technology. Each of these exogenous sources has been widely investigated in the literature, but the novelty of this paper is in analysing them jointly in an internally coherent method.

We use a model that extends the life-cycle models of Keane and Wolpin (1997, 2010) into a unified framework of individual and family decisions following the cooperative household model, as in Chiappori (1988, 1992) and Mazzocco et. al. (2007).[1] Men and women make their decisions as individuals from age 17 to age 65, and they interact with others through the marriage market.[2] The model is estimated using March CPS data by cohorts. We discipline the analysis by holding preference parameters fixed across cohorts, which enables us to achieve identification via changes in the exogenous sources.

Aggregate data shows that the entire rise in female employment from 1962 to 2014 was concentrated among married women, and that the marriage rate decrease from 79% to 63% (figure 1).[3] These changes are almost entirely due to cohort differences (see figure 2). It is less well-known that the characteristics of married vs. single individuals have changed greatly over the past 50 years. For example, while education of all women has increased over the past 50 years, that of married women has increased much more than that of single women. Similarly, for women the married/non-married wage premium (conditional on age and education), has gone from about -10% in the 1935 cohort to +7% in the 1975 cohort (figure 4).[4] Thus, over the past 50 years, selection of women into marriage based on labor market skills has gone from strongly negative to strongly positive. Similarly, the average education of married men has increased substantially relative to that of single men.

[1] Gemici and Laufer (2011) build on Mazzocco et. al. (2007), and they estimate a dynamic model of household marriage, divorce, fertility and labor supply decisions.

[2] Recent papers connecting the marriage market and education decisions are Chiappori at el. (2009, 2015) and Ge (2011).

[3] See section 2 for more details of these motivating facts.

[4] This is consistent with the finding of Muligan and Rubinstein (2008) that the correlation of selection of females to employment with their skills changed from negative to positive.

The literature includes many explanations for these changes in decisions and outcomes for both men and women over time. For example, explanations for why married women now have fewer children and participate more in the labor market include: reduced gender wage discrimination (Jones at el. (2003)), improvements in birth control (Goldin and Katz (2002)), changing divorce laws (Stevenson (2008), Voena (2011)), increased demand for female labor (i.e., growth of the service sector as in Lee and Wolpin (2006)), improvements in household technology (Greenwood and Seshadri (2005), Greenwood at el.(2005)) and changing social norms about gender roles.[5]

To measure the contribution of each of the five potential sources mention above, we structurally estimate the preferences of individuals using our life-cycle model using data on the cohorts of 1945, 1955 and 1965. We then allow the exogenous sources to be different for each cohort in a sequence, until we obtain a good fit to all the decisions of all cohorts. The fit analysis using the exogenous processes is also done for the cohorts of 1935 and 1975. Here we summarize our main results, focussing on major changes from the 1935 to 1975 cohorts, and stating how our estimated model explains the contribution of each source:

Education. The percentage of women who are at least college graduates increased from 6% in the 1935 cohort to 37% in the 1975 cohort. The key factor driving this increase is increased mother's education which affects individual unobserved skills and tastes for education. It accounts for more than 40% of the change. Two additional key factors are lower divorce costs and better labor market prospects for women (as captured by changes in the wage offer function and job offer rates).

The education level of men also increased, but not nearly as much as for women. The percentage of men who are at least college graduates increased from 21% in the 1935 cohort to 29% in the 1975 cohort. The model implies that half of this increase was due to lower divorce costs. It is often argued that higher divorce rates raise the incentive for women to acquire human capital. But the same is true for men, as a higher divorce rate increases the risk that one may have to live as a single without the benefits of economies of scale from joint household production.

Marriage. Between the 1935 and 1975 cohorts, the marriage rate for 25-34 year olds fell by 28%, while that for 35-44 year olds fell by 15%. We find that increased mother's education, which has the primary effect of increasing women's own education, accounts for about 2/3 of the reduction of marriage at early ages, and 40% for 35-44 year olds.

[5] Also, note that what we refer to as "compositional" vs. "behavioral" effects may interact. For example, changes in the supply of college educated women may change gender roles in equilibrium, and vice versa.

Divorce. The divorce rate increased by 302% at ages 25-34, and by 85% at ages 35-44. The model implies that at older ages the increase in the divorce rate was almost entirely due to the reduction in divorce costs. But at younger ages increased women's education and availability of contraception also play important roles.[6]

Fertility. The average number of children for married women aged 35-44 fell by 17%, while for younger married women (25-34) the drop is much larger (44%). This is indicative of delayed fertility. Availability of oral contraception explains most of the drop in *completed* fertility for married women, but economic factors (i.e., higher education, lower divorce costs, higher wage offers, changes in the marriage market) explain most of the *delay* in fertility. Fertility of unmarried women fell much more sharply than for married women. The model implies that the large drop in children for unwed women was almost entirely due to the availability of oral contraception.

Wages. Both levels of initial wages and returns to education were much smaller for women than for men in the 1935 cohort. But by the 1975 cohort the wage structure for women was quite similar to that for men. This had a major positive effect on women's labor supply. The wages of (employed) married women increased substantially (81% at ages 25-34, 100% at ages 35-44). The model implies only a small fraction of this increase was due to increased women's education. Most was due to changes in the wage structure that increased their relative wages at all levels of education, and that increased their returns to education.

Employment. The employment rate of married women aged 25-34 increased by 110%. The model implies that roughly 2/3 of this increase was due to changes in the wage/employment structure while about 1/3 was due to oral contraception. Single men work less than married men. And there is a small drop in the employment rate across cohorts. The model fits both of these patterns well. However, it is notable that, in contrast the major changes we observe for married women, the behavior of both men and single women is relatively stable in most respects across these cohorts. It is a success of the model that it is able to generate the very large changes we observe for married women, while simultaneously capturing the relatively stable behavior of both men and single women.[7]

Marriage premium. The marriage premium for women shifted from -10% to +7%. The model is able to explain roughly ¾ of this change, which was not a targeted moment. The main factors are (i) increased mother's education that affects initial skills, and (ii) changes in

[6] Recent papers that empirically analyse the link between changes in the divorce laws and labor supply are Stevenson (2008), Voena (2011**)** and Fernandez and Wong (2010, 2011).
[7] This is due to the success of the dynamic structural selection framework of the model. Using a static Heckman selection model, Mulligan and Rubinstein (2008) find that selection has changed dramatically over time.

the offer wage distribution. Both factors imply that the higher skilled females and males are more likely to be married, and this selection is key in explaining the increase in the observed and unobserved skills of married females, which in turn enhances their employment.

Given that background, we now proceed with the analysis. In Section II we describe the data that we use, and describe some of the key changes in behavior that we observe over the 1962 to 2014 period. In Section III we present our life-cycle model of labor supply, marriage and fertility. It is well-known that structural modelling of fertility is extremely difficult, because the introduction of children of different ages into the life-cycle model leads to an explosion in the size of the state space. As a methodological contribution, we present a new way of modelling fertility that avoids this problem.

In Section IV we describe the solution of the model. Solving a marriage market model in a dynamic non-stationary environment is in general a serious computation problem. We also present some innovative techniques to simplify this problem. Section V presents our estimation method (method of simulated moments) and discusses identification.

We present our empirical results in Section VI. We emphasize the counterfactual experiments that we use to decompose observed changes in life-cycle decisions and outcomes over the sample period, and to assess the impact of different exogenous factors. Section VII concludes.

II. Key Patterns in the Data

In this section we describe several key data patterns that motivate our subsequent analysis. We use the March CPS from 1962 to 2014, and consider both Caucasian males and females aged 22-64.

II.1. *Employment Rates by marital status*

Figure 1 reports employment rates over calendar time by marital status.[8] We define "employment" as working at least as 10 hours a week. Clearly the most striking change is that the employment rate of married women doubles from about 30% in 1962 to about 60% in 1994. It then plateaus, and hovers in the low 60%s from 1994 through 2014. In contrast, the employment rate of single and divorced women, who behave quite similarly, is very stable. It hovers around 70% throughout the whole period. Thus, between 1962 and 1994, roughly ¾ of the employment gap between married and un-married women was eliminated.[9]

Figure 1 – Employment Rate by Marital Status

Figure 1.A. - Women

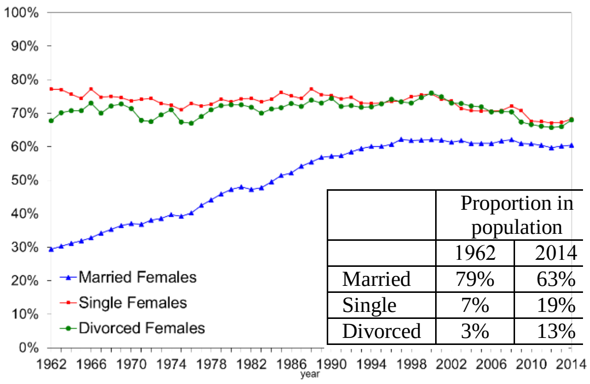
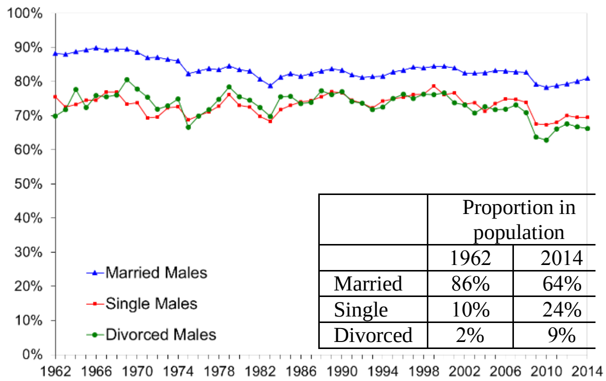


Figure 1.B. - Men



While the employment rate of married women doubled, their proportion in the population dropped from 79% to 63%, and the proportion of single and divorced women more than tripled (similar trends are observed for men).

Figure 1B reports employment rates for men. Comparing Fig. 1A and 1B, the similarity of the employment patterns of single and divorced men and women is striking. The employment rate of both single and divorced men hovers around 75% from 1962-99, and

[8] Cohabitation is considered as unmarried. We don't have data prior to 1995, but in 1995, 1.6% of the population was cohabiting and by 2014 it increased to 3.8%. In the cohort of 1975, 4.7% are cohabiting.

[9] By 1962, about 8% of the women were working in part time jobs (less than 35 hours a week), in 2014 this proportion doubled. This is true for married, single and divorced women. The proportion of married women working full time doubled in this period (22% to 44%), while for divorced (single) women the proportion of women working full time dropped from 59% (70%) to 53% (50%). For details see the supplemental web site at http://www1.idc.ac.il/Faculty/Eckstein/EKL.html).

decreases slightly after 2000. In contrast, married men work more than single men or women. Their employment rate was near 90% in the 1960s. It fell both in the recession of 1974-1975, and in the recession of the early 1980s. After that, the employment rate of married men never returns to its 1960s level – it instead hovers in the low 80%s from 1984 until the present.[10]

II.2. *Employment Rates by Cohort*

Figure 2 plots employment rates by cohort. We define 7 cohorts, using five year windows centered on the birth years of 1925, 1935 and so on until 1985. The striking pattern is that the employment rate increases over cohorts only for married women. There are no substantial differences across cohorts for un-married women, married men or un-married men[11] (here we combine the divorced and single categories as they behave very similarly).

For married women the difference in behavior between the 1955 cohort and earlier cohorts is 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.[12]

Figure 2 – Employment Rate by Cohort and Marital Status

Figure 2.A. – Married Women

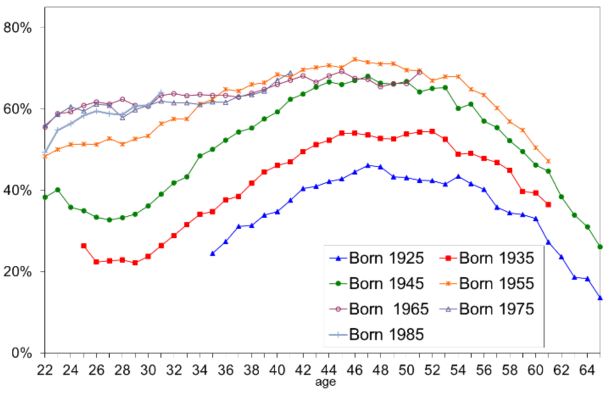
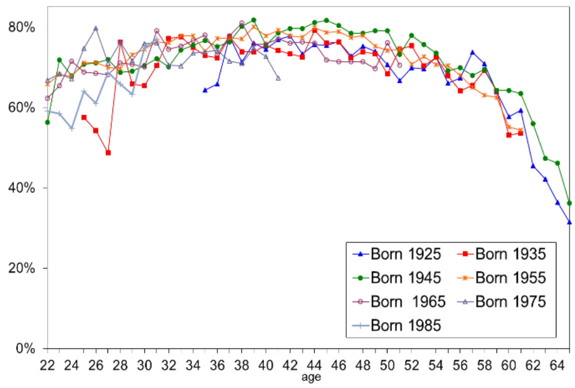


Figure 2.B. – Unmarried Women



The 1965 cohort takes a bit further the changes that occurred between the 1945 and 1955 cohorts. The employment rate in the early 20s is a few points higher, and the

[10] Cyclical patterns are clear in Figure 1. In particular the Great Recession (2009-2011) causes employment rates to fall for all groups. It is interesting that cyclical patterns are strongest for un-married men, and weakest for married women. Both single and divorce men and women have higher unemployment rates than married men and women (see http://www1.idc.ac.il/Faculty/Eckstein/EKL.html).

[11] The figures for men and the figures by detailed marital status (divorce, single, etc.) can be found at the website http://www1.idc.ac.il/Faculty/Eckstein/EKL.html.

[12] 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%).

employment rate in the prime childbearing years (mid-to-late 20s) is several points higher.

A notable feature of the data for married women is that the cohorts after 1955 behave very similarly. Thus, it appears that the historic increase in employment of married women in the 20^{th} century was essentially complete by the 1965 cohort. This is consistent with the flatness in aggregate employment of married women after 1995 (see Figure 1A).

Of course, it is difficult to determine whether the different behavior of married women across cohorts is due to cohort differences (e.g., different attitudes toward married women working across generations) or due to time differences (e.g., changes in home production technology, changes in demand for female labor). We will need to use more structure and look at more data patterns to disentangle alternative explanations.

Interestingly, we also plotted employment rates for divorced women *with children* (not shown). We find that their employment was very stable across all 7 cohorts. The similar behavior of divorced women with children born 60 years apart may be problematic for theories that emphasize changes in home production technology and child cost as a reason for increased female employment. Under those theories we might expect to see similar patterns for married women and divorced women with children. However, this is not obvious, because the composition of the group of divorced women with children has changed, and the economic conditions faced by this group, have presumably changed as well.

Finally, male employment rates by cohort (not shown) are stable for both married and single men. One exception is that the Great Recession has a clear effect on employment rates in the years 2008-2011 for the 1965, 1975 and 1985 cohorts.

In summary, a major challenge for any model that seeks to explain the great increase in the employment rate of married women is to *simultaneously* explain the remarkable stability of the employment rates of both un-married women and men. Another challenge is to capture the timing – i.e., the fact that the increase in married women's employment was complete by the 1965 cohort (or by roughly 1995 in the aggregate data).

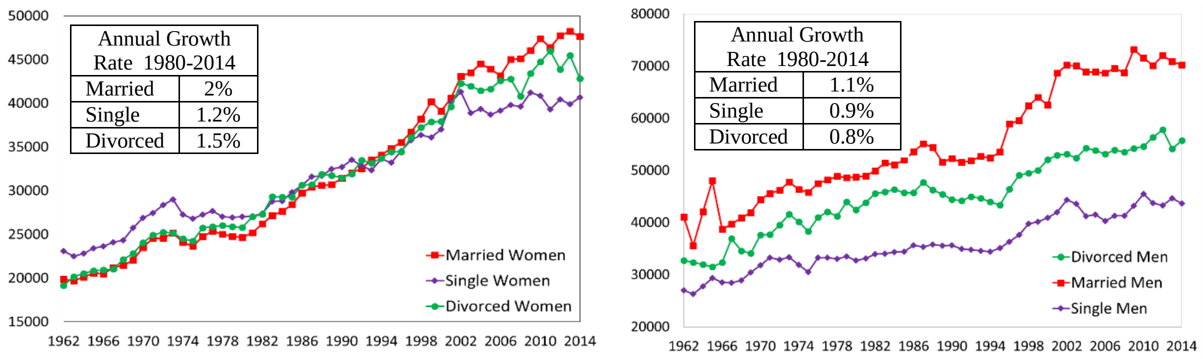
II.3. *Changes in Wages over Time*

Figure 3 plots annual earnings of full-time workers. Again, we separate men and women and those who are married, single or divorced. In 1962, the full-time wage of single women was roughly 15% higher than that of married women. But by 2014 this is reversed, and the full-time wage of married women is roughly 18% higher than for single women. The point where wages of married women pass those of single women is 1992. An interesting detail is that until the mid-90s divorced women look very much like single women, but then their relative wages start to grow and by 2014 they look more similar to married women.

Figure 3B shows earnings patterns for men. The ranking of married, divorced and single men by the annual wage is very stable, but the magnitude of the gaps grow over time. In 1962, the full-time wage rate for married men was roughly 33% higher than that for single men, with divorced men roughly in the middle. But by 2014 the annual wage rate of married men is 66% greater than for single men.

Figure 3 – Annual Wages by Marital Status

3.A - Women **3.B - Men**



Thus, we see that the extent of assortative mating (by earnings) increases greatly over the 50-year period. In 1962 the annual wage of married men was 33% higher than that of single men, but the annual wage of married women was 15% lower. By 2014 the annual wage rates of married men and women are roughly 66% and 18% greater, respectively, than those of single men and women.

Part of the wage gap reversal between married and non-married women is due to a change in their observable characteristics: education and experience. The increase in married women's employment rate decreases the experience gap between married and non-married women. Moreover, married women became more educated than non-married women. In 1964, only 7% of married women had a college degree or more, compared to 10% of un-married women. By 2014 this pattern had reversed, and 36% of married women had a college degree or more, compared to only 28% of un-married women.[13, 14] But education and experience can explain only part of the wage gap reversal between married and non-married women. We next look at how un-observed characteristics, as captured by the so-called "marriage wage premium," changed over time.

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[13] Goldin et al. (2006) analyse the reversal of the college gender gap.

[14] The figures describing the education levels for both men and women by marital status can be found at the website http://www1.idc.ac.il/Faculty/Eckstein/EKL.html.

II.4. *Changes in Marriage Wage Premia by Cohort*

The "marriage wage premium" is conventionally defined as the coefficient on a marriage dummy included in a standard Mincer earnings equation. That is:

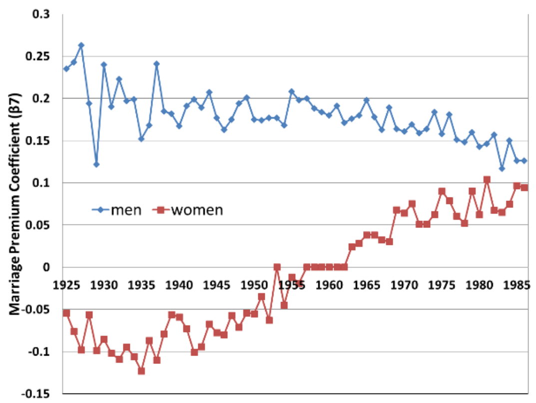
$$\ln(W_i) = \beta_0 + \beta_1(age - school)_i + \beta_2(age - school)_i^2 + \beta_3 HSG_i + \beta_4 SC_i + \beta_5 CG_i + \beta_6 PC_i + \beta_7 M_i + u_i$$

where *HSG*, *SC*, *CG* and *PC* are dummies for education levels, from high school graduate to post-college. We estimated such regressions annually by year of birth for both men and women. Figure 4 reports the coefficients (β_7) on the marriage dummies M_i.

Consider first the results for women. For cohorts born in the 30s and 40s, married women earned 5 to 10% *less* than single women. But for cohorts born in the 70s and 80s, the wages of married women are roughly 5 to 10% *higher* than those of single women. Thus, the wage premium for married vs. single women turned from clearly negative to clearly positive in two generations.

The marriage premium for men also changed over the past 50 years, but much more modestly. As we see in Fig. 4, for cohorts born in the 20s and 30s, married men earned about 20% more than single men. But for the cohorts born in the 80s, this has been reduced to 15%.

Figure 4 – Wages by Marital Status



In contrast to this drop in the marriage premium, recall from Figure 3 that the annual wage premium of married over single men rose from 33% in 1962 to 66% in 2014. However, in Figure 3 we did not control for education while in Figure 4 we do, so this (apparent) contradiction can be explained by the increase in the education of married vs. unmarried men.

From Figures 1-4, we conclude that both observed and unobserved characteristics of married men and women changed dramatically over the sample period. In Section III we present the structural model that we use to interpret the data, and which we hope can account for these and other changes that we observe over the sample period.

III. A Life-Cycle Model of Labor Supply, Marriage and Fertility

In this section we present the model that we use to analyse the data patterns discussed in Section II. In our model, men and women start out as single individuals at age 17 in school, who make private decisions about school continuation, work, and, in the case of women, fertility. The men and women in the model also interact in a marriage market, so they can choose to form (and later dissolve) couples. Once a couple is formed, decisions about labor supply and fertility are made jointly.

In order to make marriage decisions, individuals must compare the value of remaining single vs. the value of being married. So for us to model the marriage decision, we must first obtain the values of the married and single states. Thus, we first describe the problem of married couples (Section III.A), followed by that of single individuals (Section III.B). We are then in a position to explain how we model the marriage market (Section III.E).

III.A. The Problem of a Married Couple

We first describe the optimization problem of a married couple. We begin by defining the choice set, then constraints and preferences, and finally the solution method (we assume a collective model of household decision making, as we explain below).

Let t denote the (annual) time period, and let $j = f, m$ denote gender. Individuals have time endowments of 1 unit per period. This time is split between market work (h) and home time (l), so $h_t^j + l_t^j = 1$. In each period an individual can work full-time, part-time, or not at all. Thus, $h_t^j \in \{0, 0.5, 1.0\}$. Symmetrically, individuals have a level of home time given by $l_t^j = T - h_t^j$ for $j=f,m$. To be concise we will often refer to l_t^j as simply "leisure," but bear in mind that it also includes home-work and other non-leisure activities. Given our three level partitioning of work hours, the choice set for leisure is $l_t^j \in \{0, 0.5, 1.0\}$.[15]

Conditional on marriage, couples have three choice variables: The levels of home time for the husband and wife, $\{l_t^m, l_t^f\}$, and pregnancy, indicated by p_t. For simplicity we assume the decision to have a pregnancy leads deterministically to arrival of a child in the next period. Letting X_t^j denote work experience, and N_t denote the number of children under 18, the laws of motion for these state variables are:

$$X_{t+1}^j = X_t^j + h_t^j \qquad j = m, f$$

$$N_{t+1} = N_t + p_t - p_{t-18}$$

[15] This normalization is without loss of generality. The mapping from the three levels of leisure (or home time) to utility is only constrained once we choose a parametric utility function.

In addition to work and fertility, couples also make annual decisions about whether to remain married or get divorced. We ignore this for the time being and focus on the joint decisions of couples *conditional* on marriage.

III.A.1. *Preferences and Constraints*

Married couples have total income Y_t^M given by the equation:

$$(1) \qquad Y_t^M = w_t^m h_t^m + w_t^f h_t^f + b_m I[h_t^m = 0] + b_f I\left[h_t^f = 0\right]$$

Here w_t^j and h_t^j for $j=f,m$ are wage rates and hours of work, while b_j is the unemployment benefit plus the value of home production. We will use the M superscript throughout to indicate values for married individuals.

The household budget constraint takes the form:

$$(2) \qquad C_t^M = (1 - \theta(N_t))Y_t^M$$

Here N_t denotes the number of children under age 18. The parameter $\theta(N_t)$ is the fraction of household income that is spent on children. We use the square root equivalence scale to determine $\theta(N_t)$.[16]

The per-period utility of a <u>married</u> individual of age t and gender j is given by:

$$(3a) \qquad U_t^{jM}(\Omega_{jt}) = \frac{1}{\alpha}(\psi C_t^M)^\alpha + L_j\left(l_t^j\right) + \theta_t + \pi_t^M p_t + A_j^M Q\left(l_t^f, l_t^m, Y_t^M, N_t\right) \qquad j = m, f$$

where:

$$(3b) \qquad L_j\left(l_t^j\right) = \frac{\beta_{jt}}{\gamma}\left(l_t^j\right)^\gamma + \mu_{jt} l_t^j \qquad \gamma < 1, \alpha < 1$$

The first term in (3) is a CRRA in consumption with curvature parameter α. We assume household consumption C_t^M is a "public" good. That is, the full amount C_t^M enters the utility of both the husband and wife. The parameter $\psi \in (½, 1)$ captures household economies of scale in consumption.[17] We adopt the widely used "square root" equivalence scale, which gives $\psi = 1/\sqrt{2} = 0.707$. This implies that a couple needs only 41% more expenditure than a single person to obtain an equivalent consumption level.

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[16] For a household with two adults, the square root scale implies that $\theta(N) = 1 - \sqrt{2/(2+N)}$. Thus, $\theta(N)$ = 0.194, 0.293, 0.367 and 0.423 if N = 1, 2, 3 or 4, respectively. We impose that 4 is the maximum number of children, as few people in the data have more, and this helps reduce the state space size.

[17] If $\psi = ½$ there are no economies of scale, while if $\psi = 1$ a couple receives the same equivalent consumption as a single individual for any given expenditure level.

The second term in equation (3) is a CRRA in leisure with curvature parameter γ. The parameter β_{jt}, which must be positive, shifts tastes for leisure. For women we allow β_{jt} to depend on p_t, while for both men and women we allow β_{jt} to depend on parents' education and on health status. Allowing health status to affect tastes for leisure is an important feature of the model, as it helps to generate retirement behaviour. Stochastic variation in the marginal utility of leisure is captured by the term $\mu_{jt} l_t^j$ where μ_{jt} is a random variable.

The last three terms in (3) are needed to model marriage, fertility and child investment decisions: The third term (θ_t) is the utility the individual derives from marriage itself (i.e., the match quality), the fourth term captures the utility (or dis-utility) from pregnancy (p_t=1), and the fifth term captures the utility a couple receives from the quality and quality of children.

We now discuss the specific functional forms of the tastes for leisure, marriage, fertility and children terms that appear in equation (3):

Our specification of the stochastic process for tastes for leisure (μ_{jt}) is an important aspect of our model. Specifically, we assume that:

$$(4) \qquad \ln(\mu_{jt}) = \tau_{0j} + \tau_{1j}\ln(\mu_{j,t-1}) + \tau_{2j}p_{t-1} + \varepsilon_{jt}^{l} l_t^{j} \qquad where \qquad \varepsilon_{jt}^{l} \sim iidN(0, \sigma_{\varepsilon}^{l})$$

where $0 < \tau_{1j} < 1$. Thus, shocks to tastes for leisure (i.e., home time) follow a stationary AR(1) process. Importantly, the arrival of a new child at time t (i.e., if p_{t-1}=1) leads to a shift in tastes for home time (τ_{2j}).

In practice we would expect that, at least for women, the marginal utility of home time will jump up when a newborn arrives (i.e., $\tau_{2f} > 0$). Afterward, provided that no new children arrive, tastes for home time gradually revert back to normal (because $\tau_{1f} < 1$). This mechanism enables the model to generate relatively large declines in employment for women after childbirth, as well as their subsequent return to the labor force as children grow older. However, the stochastic terms ε_{jt}^{l} generate heterogeneity in individual response patterns.

The specification in (4) has important advantages over prior approaches to modelling fertility. In general, in dynamic models with endogenous fertility, a person's state vector contains the number of children at each specific age. As a result, the number of possible state vectors is astronomical.[18] This problem has always made dynamic modelling of fertility very challenging. Our approach circumvents this problem. Given the specification in (4), the state

[18] In prior work it has been typical to assume that children affect tastes for leisure through the parameter β_{jt}, which is assumed to depend, in a deterministic way, on the number and ages of children. This causes the state space to explode. See Geweke and Keane (2001) for a detailed discussion of this problem.

space of an individual in our model only contains the scalar variable μ_{jt} rather than the entire vector of ages of all children. This leads to very great computational savings.

Next consider the utility from marriage (θ_t) – i.e., the match quality. We write:

$$\text{(5)} \qquad \theta_t = d_1(E^m - E^f = 0) + d_2(E^m - E^f > 0) + d_3(E^f - E^m > 0) + d_4(H^m - H^f)^2 + \mu^M + \varepsilon_t^M \quad \text{where} \quad \varepsilon_t^M \sim iidN(0, \sigma_\varepsilon^M)$$

The first three terms in (5) capture assortative mating based on education. If d_1>0 then people prefer matches where education of the partner is similar to their own. But if d_2>0 (d_3>0) then people prefer matches where the male (female) has more education. The next term captures assortative mating based on health. If d_4<0 then people prefer matches where health of the partner is similar to their own. The term μ^M is a match quality draw that persists for the duration of the match. Finally, ε_t^M is a transitory shock to match quality. Negative values of this shock are one factor that drives divorce.

Next consider the utility from pregnancy, π_t. We specify that:

$$\text{(6)} \qquad \pi_t = \pi_1 m_t + \pi_2 H_{ft} + \pi_3 N_t + \pi_4 p_{t-1} + \varepsilon_t^p \text{ where } \varepsilon_t^p \sim iidN(0, \sigma_\varepsilon^p)$$

The value of π_t is a function of marital status, where m_t is a 1/0 indicator for marriage. It is also a function of health (e.g., pregnancy risks differ by women's health), the number of children (tastes for children depend on the number already present) and lagged pregnancy. And ε_t^p is a stochastic shock to tastes for pregnancy.

Note that equation (6) contains nothing individual specific. We assume pregnancy decisions are made jointly by the couple, and each party gets the same utility from the decision. Of course, one could imagine individuals in a couple getting different utilities from a pregnancy decision, but we cannot infer such differences from the data so we ignore them.

Finally, consider the function $Q(\cdot)$ that determines the utility a couple receives from the quality and quantity of children. We assume it is a CES function of the inputs, as follows:

$$\text{(7)} \quad Q\left(l_t^f, l_t^m, Y_t^M, N_t\right) = \left(a_f\left(l_t^f\right)^\rho + a_m(l_t^m)^\rho + a_g(\theta(N_t)Y_t^M)^\rho + (1 - a_f - a_m - a_g)N_t^\rho\right)^{1/\rho}$$

The first three inputs, which are home time of parents and spending per child, $\theta(N_t)Y_t^M$, all increase child quality. The parameter A_j^M in the utility function (3) is a scale parameter that multiplies $Q(\cdot)$. This parameter is allowed to differ in the single state (see below).

We are now able to write the choice-specific value functions for married *individuals*. These depend on both a person's own state and that of their partner:

$$(8)\quad V_t^{jM}\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) = \frac{1}{\alpha}(\psi C_t^M)^\alpha + L\left(l_t^j\right) + \theta_t + \pi_t p_t + A_j^M Q\left(l_t^f, l_t^f, Y_t^M, N_t\right)$$

$$+\delta E\left(m_{t+1}V_{t+1}^{jM}\left(\Omega_{m,t+1}, \Omega_{f,t+1}\right) + (1-m_{t+1})V_t^j\left(\Omega_{j,t+1}\right)\right) \qquad j = f, m$$

The current payoff in (8) simply reproduces (3). The future component of the value function in (8) consists of two parts, corresponding to whether the marriage continues at t+1 or not. The term $V_{t+1}^{jM}\left(\Omega_{m,t+1}, \Omega_{f,t+1}\right)$ is the value of next period's state for partner j given that the marriage continues. The newly defined term $V_t^j\left(\Omega_{jt+1}\right)$ is the value of next period's state for partner j if he/she becomes single (i.e., a divorce occurs). We discuss divorce decisions below, and the value functions for single persons in Section III.B.

Note that next period's state depends on the current state $\{\Omega_{mt}, \Omega_{ft}\}$ and current choices $\left\{l_t^m, l_t^f, p_t\right\}$ through the laws of motion of the state variables. The parameter δ is the discount rate and $E(\cdot)$ is the expectation operator. The expectation is taken over elements of the t+1 state that are unknown at t. These include m_{t+1}, $\left\{\varepsilon_{jt+1}^l\right\}$ for j=m,f, ε_{t+1}^M and ε_t^p. In addition, there are also realization of wage shocks and job offers. We defer a detailed discussion of these until Section III.C which describes the labor market.

III.A.2. *Household Decision Making*

We adopt a collective model of household decision making. The partners choose leisure and fertility to maximize the value function:

$$(9)\quad V_t^M\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) = \lambda V_t^{fM}\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) + (1-\lambda)V_t^{mM}(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft})$$

Here λ and (1-λ) are Pareto weights. The $V_t^{jM}\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right)$ for j=f,m are the choice-specific value functions of the *individual* married partners. The Ω_{jt} for j=f,m are the state vectors of these individuals. Couples seek a choice vector $\left\{l_t^m, l_t^f, p_t\right\}$ that maximizes (9).

However, the maximization of (9) is subject to the constraint that both parties must prefer marriage over the outside option of divorce. Let $V_t^m(\Omega_{mt})$ and $V_t^f(\Omega_{ft})$ denote the maximized value functions of single males and females in period t. We assume that a divorce occurs if the value of the outside (single) option exceeds the value of marriage for either party. Let $\mathcal{F}$ denote the feasible set of choice options. A choice vector $\left\{l_t^m, l_t^f, p_t\right\} \in \mathcal{F}$ if:

$$(10) \qquad V_t^{jM}\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) \geq V_t^j\left(\Omega_{jt}\right) - \Delta_{jt} \quad for \quad j = f, m$$

where Δ_{jt} denotes the cost of divorce. Thus we have that:

$$\mathcal{F} = \left\{l_t^m, l_t^f, p_t \middle| V_t^M\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) \geq V_t^j\left(\Omega_{jt}\right) - \Delta_{jt} \, for \, j = m, f\right\}$$

Note that $\mathcal{F} = \emptyset$ if no choice vector $\{l_t^m, l_t^f, p_t\}$ satisfies (10).

We can now proceed to formally define the solution to the maximization problem. Denote the vector of household choices that maximize equation (9) as $\{l_t^{m*}, l_t^{f*}, p_t^*\}$. That is,

$$\{l_t^{m*}, l_t^{f*}, p_t^*\} = \begin{cases} arg\max_{\{l_t^m, l_t^f, p_t\} \in \mathcal{F}} V_t^M\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right) & if \quad \mathcal{F} \neq \emptyset \\ \emptyset & if \quad \mathcal{F} = \emptyset \end{cases}$$

The form of (9) insures that $\{l_t^{m*}, l_t^{f*}, p_t^*\}$ is a Pareto efficient allocation of resources within the household.[19] If one or more parties prefer to remain single for all settings of $\{l_t^m, l_t^f, p_t\}$ then $\mathcal{F} = \emptyset$ and $\{l_t^{m*}, l_t^{f*}, p_t^*\} = \emptyset$.

In Section III.C we describe how additional constraints on the feasible set $\mathcal{F}$ arise because of the structure of the labor market. Specifically, in each period workers receive full and part-time job offers with certain probabilities, so not every leisure/work-hours choice $\{l_t^m, l_t^f\}$ is available. An interesting point is that constraints on the choice set will, in general, affect marriage and divorce probabilities.

We now define the maximized value function of a married *individual* in state Ω_{jt} as:

$$(11) \quad V_t^{jM}\left(\Omega_{mt}, \Omega_{ft}\right) \equiv \begin{cases} V_t^{jM}\left(l_t^{m*}, l_t^{f*}, p_t^* | \Omega_{mt}, \Omega_{ft}\right) & for \quad j = f, m \quad if \quad \mathcal{F} \neq \emptyset \\ -\infty & for \quad j = f, m \quad if \quad \mathcal{F} = \emptyset \end{cases}$$

Note that the maximized value function depends not only on Ω_{jt} but also on the state vector of the partner. This dependence arises from two sources: First, the individual choice-specific value functions of married people $V_t^{jM}\left(l_t^m, l_t^f, p_t | \Omega_{mt}, \Omega_{ft}\right)$ depend on the state of both the individual and his/her partner. Second, the fact that $\{l_t^{m*}, l_t^{f*}, p_t^*\}$ is a joint decision made by the couple, so it depends on $\{\Omega_{mt}, \Omega_{ft}\}$. Note also that if $\mathcal{F} = \emptyset$ then no action exists such

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[19] If we simply take the *unconstrained* maximum of (9), we could potentially obtain a solution for $\{l_t^m, l_t^f, p_t\}$ where one party prefers to be single rather than married. But in a transferable utility framework marriage may still be supportable in such a case, using transfers between partners. But do not adopt this approach, because it is not clear how such transfers would be enforceable after a couple agrees to remain in the married state.

that person j can be married at time t. In that case V_t^{jM} is set to -∞; then their behaviour is governed solely by the properties of the single value function $V_t^j(\Omega_{jt})$.

Finally, we discuss divorce decisions in more detail. A divorce occurs in period t if:

$$(12)\qquad V_t^f(\Omega_{ft}) - \Delta_{ft} > V_t^{fM}(\Omega_{ft}, \Omega_{mt}) \qquad or \qquad V_t^m(\Omega_{mt}) - \Delta_{mt} > V_t^{mM}(\Omega_{ft}, \Omega_{mt})$$

Where Δ_{jt} is the cost of divorce which may change over calendar time due to changing divorce laws.[20] In our framework, the couple seeks to maximize (9) subject to the constraint that neither inequality in (12) holds.

In the next section we discuss the construction of the value functions for single people, which we denote as $V_t^j(\Omega_{jt})$, in detail. We will discuss the marriage market and marriage decisions in Section III.E.

III.B. The Problem of Single Households

In this Section we describe the optimization problems of single (i.e., unmarried) men and women. To begin, note that the income of a single person is simply:

$$(13)\qquad Y_t^j = w_t^j h_t^j + b_j \cdot I[h_t^j = 0] + cb_t(N_t) \cdot I(j = f, N_t > 0) \qquad for\ j = m, f$$

As in equation (1), w_t^j and h_t^j for j=f,m are wage rates and hours of work, respectively, while b_j is the unemployment benefit (plus value of home time). The term $cb_t(N_t)$ is new. It is a function designed to capture the array of social benefits for single mothers in the U.S..[21] These include welfare benefits, child care subsidies, etc. As modelling these sources of benefits is extremely complex (see Keane and Moffitt (1998), Keane and Wolpin (2010)), we treat $cb_t(N_t)$ as an exogenous stochastic process that we fit from the data prior to estimation (see Appendix B for details).

The benefit rule $cb_t(N_t)$ provides a natural exclusion restriction. Benefits affect the behaviour of single women *directly* through the budget constraint. But they only affect the behaviour of married women, and all men, *indirectly*. These indirect effects operate through the marriage market and the household bargaining process.[22]

[20] In the model we abstract from marriages that end via the death of a spouse. The terminal period in the model is age 65, at which point we assume everyone retires. We assume everyone lives to that age.

[21] Historically, welfare benefits in the U.S. were heavily targeted toward single women with children, who were often viewed as a "deserving" group (see Katz (1989)).

[22] There is a static literature that examines effects of welfare rules on marriage and divorce. Bruins (2016) uses a collective model of the household to examine the effect of welfare rules on the allocation of consumption within marriage.

The budget constraint for a single person is simply:

(14) $$C_t^j = (1 - \theta(N_t))Y_t^j$$

This differs from (2) only in that we drop the marriage cost. Notice that both single men and women may have children (N_t >0). These may be children from a previous marriage or, in the case of single women, children born outside of marriage.

Turning to the utility function, we adopt a view of the world in which utility functions exist at the individual level, and they are not fundamentally altered by marriage. Recall that in marriage, household decisions are made by constrained maximization of a weighted average of the individual partners' utility functions, as in (9). Consistent with this view, we specify the utility function for singles to be as similar as possible to that of married people.

Consider the per-period utility function of a single female:

(15) $$U_t^f(\Omega_{ft}) = \frac{1}{\alpha}(C_t)^\alpha + L_j(l_t) + \vartheta_{ft}s_t + \pi_t p_t + A_f^s Q(l_t, 0, Y_t, N_t)$$

This is very similar to the utility function of a married woman, as one can see by comparing (3) and (15). The only changes are that consumption is now individual specific (i.e., the equivalence scale ψ = 1), the utility from marriage term is (of course) dropped, the utility from children is allowed to differ from the married state ($A_f^s \neq A_j^M$), and, of course, the home-time of the husband is set to zero in the Q function.

We also make the simplifying assumption that only single people can attend school (as school attendance by married people is rare in the data).[23] Thus, we include in the utility function (15) a term for the utility from school attendance. We let s_t be an 1/0 indicator for school attendance, while ϑ_{ft} captures tastes for school attendance.[24] Specifically:

$$\vartheta_{ft} = \vartheta_{0f} + T \cdot I(E_t > HSG) + \vartheta_{1f}PE + \vartheta_{2f}\mu_f^W$$

Here ϑ_{jt} is a function of tuition cost T, which is only relevant for higher education, the skill endowment μ_f^W, and education of the person's parents, denoted PE. The dependence of tastes for school on parents' education helps to generate changes in education levels across cohorts.

[23] We also rule out school attendance after age 30 for the same reason, as in Keane and Wolpin (1997).

[24] Note that ϑ_{ft} captures the utility of school minus the cost. Without data on costs these can't be identified separately.

We can now write the choice-specific value functions for single females:

(16a) $V_t^f(l_t, p_t, s_t|\Omega_{ft}) = \frac{1}{\alpha}(C_t)^\alpha + L_f(l_t) + \vartheta_{ft}s_t + \pi_t p_t + A_f^s Q(l_t, 0, Y_t, N_t) + \delta EV(\Omega_{f,t+1})$

where:

(16b) $EV(\Omega_{f,t+1}) = E\left(m_{t+1}V_{t+1}^{fM}(\Omega_{m,t+1}, \Omega_{f,t+1}) + (1 - m_{t+1})V_t^f(\Omega_{f,t+1})\right)$

Note that the expected value function $EV(\Omega_{f,t+1})$ takes into account the possibility that the person may get married at *t*+1.

Similarly, for single males we have the choice-specific value function:

(17) $V_t^m(l_t, s_t|\Omega_{mt}) = \frac{1}{\alpha}(C_t)^\alpha + L_m(l_t) + \vartheta_{mt}s_t + A_m^s Q(0, l_t, Y_t, N_t) + \delta EV(\Omega_{m,t+1})$

Equations (16) and (17) are symmetric, except that the latter does not include a pregnancy option. The future component in (17) is defined analogously to that for women.

Now we consider the optimization problem of singles. Below, in Section III.E, we will discuss the marriage market, but first we consider decision making *conditional* on being single – i.e., the state where no marriage offer is available, or where a marriage offer has already been declined.[25] This is a necessary first step before we analyse the marriage market.

Let $V_t^m(\Omega_{mt})$ and $V_t^f(\Omega_{ft})$ denote the maximized value functions of single males and females in period *t*. Let $\mathcal{S}_t^m$ and $\mathcal{S}_t^f$ denote the feasible set of choice options for a single male and female in period *t*, respectively. As we will see in Section III.C, workers receive job offers probabilistically, so $\mathcal{S}_t^m$ and $\mathcal{S}_t^f$ may not include all possible levels of work hours and leisure. To proceed, for women we have:

(18) $$V_t^f(\Omega_{ft}) = \max_{\{l_t, p_t, s_t\} \in \mathcal{S}_t^f} V_t^f(l_t, p_t, s_t|\Omega_{ft})$$

while for men we have:

(19) $$V_t^m(\Omega_{mt}) = \max_{\{l_t, s_t\} \in \mathcal{S}_t^m} V_t^f(l_t, s_t|\Omega_{mt})$$

The single person value functions in (18)-(19) can now be used in equation (12) that governs divorce decisions and (26) that governs marriage decisions (see Section III.E below).

[25] Note that marriage bargaining still matters for singles because they have to forecast it to decide between the marred and single states. That is why the V_{t+1}^{fM} term enters equation 16b.

III.C. The Labor Market

In this section we describe the labor market, in particular the nature of wage and job offers. The wage equations have the standard Mincer form:

$$(20) \qquad lnw_t^j = \omega_{0j} + \omega_{1j}E_t + \omega_{2j}X_t - \omega_{3j}X_t^2 + \varepsilon_{jt}^W \qquad for \qquad j=f,m$$

Here E_t is education and X_t is work experience (in years). The wage function parameters intercepts are allowed to differ between males and females. This may capture discrimination and/or that males and females are imperfect substitutes in production – so that rental rates on male and female labor differ. The error term ε_{jt}^W has a permanent/transitory structure:

$$(21) \qquad \varepsilon_{jt}^W = \mu_j^W(PE) + \tilde{\varepsilon}_{jt}^W \qquad \text{where} \qquad \varepsilon_{jt}^W \sim iidN(0, \sigma_\varepsilon^W)$$

The time-invariant error component μ_j^W can be interpreted as the person's skill endowment, as in Keane and Wolpin (1997). We allow the skill endowment to be correlated with mother's education (*PE*), as people with more educated parents are likely to have higher endowments. Recall from III.B that the skill endowment is also allowed to affect taste for school

The size of the state space is increasing in the number of skill endowment types and the number of education types. We assume there are five possible education levels (post-graduate, college graduate, some college, high school graduate, high school dropout) and three initial skill endowment levels (low, medium, high). The probability that a person is each of the three skill types is allowed to depend of parents' education (*PE*).

We assume an unemployed individual receives at most one job offer per period. It may be a full-time offer or a part-time offer. Thus, in each period an individual faces one of three possible choice sets for hours: D = {0}, {0, 0.5} or {0,1}. Index these by k=1,2,3, and let D_{kt} = 1 if choice set k is available to an individual at time t (and 0 otherwise). We specify that the probability that each of the three choice sets is offered is determined by a trinomial logit model:

$$(22) \qquad P_j(D_{kt}) = \begin{cases} exp\left(\rho_{jk0} + \rho_{jk1}E_t + \rho_{jk2}X_t + \rho_{jk3}H_t\right)/IV_{jt} & k = 2,3 \\ 1/IV_{jt} & k = 1 \end{cases}$$

where:

$$IV_{jt} \equiv 1 + \sum_{k=2}^{3} exp\left(\rho_{jk0} + \rho_{jk1}E_t + \rho_{jk2}X_t + \rho_{jk3}H_t\right)$$

Here the probability of each choice set depends on education, work experience and health. An employed individual may lose his job, where the probability job loss is a function of the same three variables (education, work experience and health), and follows a similar logit function.

In each period a person may be unemployed because he/she draws the empty choice set (that is D_{1t} = 1 so that D = {0}), or because he/she has a part-time or full-time offer (that is D_{kt} = 1 for k=1 or 2) and rejects it.

III.D. Health Status

Health status enters the model in several places – i.e., as a shifter of tastes for work (eqn. 3b), match quality (eqn. 5), pregnancy (eqn. 6) and job offers (22). We treat health status as an *exogenous* stochastic process. Specifically, we model health status as a three-state Markov chain, where $H_{jt} \in\{1,2,3\}$ indicates poor, fair and good, respectively. The transition probabilities differ by age and cohort, and, as the process is exogenous, the parameters of the health transition matrix are estimated outside the model.[26]

The health transition probability is a multinomial logit function of the form:

$$(23) \qquad P\left(H_{jt}=k\right)=\begin{cases} exp\left(\sum_{q=1}^{3}\chi_{jkq}\cdot I\left[H_{j,t-1}=q\right]\right)/IV_{jt}^{H} & if \quad k=2,3 \\ 1/IV_{jt}^{H} & if \quad k=1 \end{cases}$$

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

$$IV_{jt}^{H}=1+\sum_{k=2}^{3}exp\left(\sum_{q=1}^{3}\chi_{jkq}I\left[H_{j,t-1}=q\right]\right)$$

Health status is a potentially an important aspect of the model for a number of reasons. For instance, health may help to explain retirement. We require people to retire by age 65, but declining health is one factor that may induce them to retire earlier. This is because health status affects both the taste for leisure term β_{jt} in (3b), and the job offer probabilities in (22). Health may also be an important dimension upon which people sort in the marriage market (see eqn. 5). Furthermore, the assumption that health evolves exogenously (i.e., it is not affected by employment, marriage or fertility decisions) means that, in the context of our model, it generates exogenous variation in these decisions.

[26] We use the IHIS (integrated health interview series) data set for the initial health distribution at age 16 or whenever a potential partner is drawn.

III.E. The Marriage Market

The final component of the model is the marriage market. In Section III.A, we discussed the choice problem of married couples. They make choices subject to the constraint that the value to each partner of remaining married must exceed that in the single/divorced state. Conversely, single people may receive marriage offers, and they will choose to become married if they draw a good enough match. To make this decision, they must compare the value of remaining single to value of entering the married state.[27] This section describes how the matching process works.

III.E.1. *Marriage Offers*

At the start of a period a single individual may receive a marriage offer. Denote the probability of receiving an offer as $p_j^H(\Omega_{jt})$ for *j=f,m*. We assume the probability depends on gender, age (above or below 18), and whether a person is in or out of school.

A marriage offer is characterized by a vector of attributes of a potential spouse, denoted by M_{jt}. It is convenient to describe the construction of marriage offers in three steps:

First, we assume that marriage offers always come from potential spouses of the same age (t). This assumption is necessitated by technical issues that arise in solving the dynamic programming problem. We discuss these issues and how we solve them in Appendix A. Here, we simply note that we do not think this assumption will have too great an effect on the results, because the large majority of married couples are in fact close in age.[28]

Second, we draw the education level of the potential spouse. This is an important aspect of the model, as one of our main goals is to explain matching between males and females of different education levels, and how this has changed over time. We assume potential spouses have three possible education levels: high-school and below (HS), some college (SC) or college or above (C), and the probability of receiving an offer from a potential spouse of the HS, SC or C type depends on a person's own education.

Specifically, if the individual gets a marriage offer, then we draw the potential partner's education using a multinomial logit with the following latent indices:

$$(24)\quad \begin{aligned} \nu_{jt}^{C} &= \eta_{0j}^{C} + \eta_{1j}^{C} \cdot I[E^m - E^f = 2] + \eta_{2j}^{C} \cdot I[E^m - E^f = 1] + \epsilon_{jt}^{C} \\ \nu_{jt}^{SC} &= \eta_{0j}^{SC} + \eta_{1j}^{SC} \cdot I[E^m - E^f = 1] + \epsilon_{jt}^{SC} \end{aligned}$$

[27] As we saw in (16b), the value of the single state incorporates the chance of finding a good match and entering the married state in the next period. This determines the option value of being single.

[28] For the cohorts of 1955-1965, the age gap between partners is below 5 years for 78% of all couples. It is below 7 years for 87% of couple, and below 10 years for 94% of couples.

and where we make high school the base case and normalize ν_{jt}^{HS} = 0. The parameters η_{1j}^{C}, η_{2j}^{C} and η_{1j}^{SC} govern the extent to which a person is more or less likely to receive offers from potential partner's whose education differs from their own. Notice that changes in the parameters of (24) across cohorts will reflect changes in the supply of potential partners of different education levels, as well as changing tastes for partners of different types.[29]

Third, we draw the other characteristics of the potential spouse (i.e., the remaining elements of M_{jt}) from the population distribution of all potential partners within the person's own age/education cell.[30] Because we do not condition on any un-observables, we can obtain these distributions from the data. Specifically, we draw the potential partner's: health status, potential work experience, number of children, mother's education, and work status in the previous period.

We also draw five un-observables from their population distributions as specified in the model. These are: the potential partner's tastes for leisure μ_{jt} (see eqn. 4), labor market ability μ_j^W (see eqn. 21), and the match quality μ^M (see eqn. 5), and the transitory parts of the wage ($\tilde{\varepsilon}_{jt}^W$) and of the taste for marriage (ε_t^M). We assume that the stochastic terms of μ_{jt}, μ_j^W, μ^M, $\tilde{\varepsilon}_{jt}^W$ and ε_t^M are observed by both parties as part of the marriage offer. Both parties also understand which terms are permanent and which terms are only transitory.

Putting this all together, the marriage offer for a single female consists of the vector:

(25) $$M_{ft} = (E^m, H^m, X^m, N^m, PE^m, h_{t-1}^m, \mu_m^l, \mu_m^W, \mu^M, \tilde{\varepsilon}_{mt}^W, \varepsilon_t^M)$$

Offers for males (M_{mt}) are analogous. The 3-step procedure we have described generates a distribution of marriage offers conditional on a person's state.

III.E.2. *Marriage Decisions*

Given a marriage offer M_{jt}, the single person has enough information to construct the vector $(\Omega_{ft}, \Omega_{mt})$ that will be state of the couple if they do marry. That is:

$$(\Omega_{jt}, M_{jt}) \rightarrow (\Omega_{ft}, \Omega_{mt}) \qquad for \quad j = f, m$$

The potential partner also knows $(\Omega_{ft}, \Omega_{mt})$. Both parties calculate the value of marriage, denoted by $V_t^{jM}(\Omega_{mt}, \Omega_{ft})$ for $j = f, m$ in equation (11). A marriage is formed if and only if:

[29] For example, it is possible that highly educated women were not viewed as desirable on the marriage market in the early cohorts.

[30] As a practical matter, conditioning on a specific age leads to relatively small samples. Thus, we draw the elements of M_{jt} using the population who are in a plus or minus 5-year window around age t.

(26) $V_t^{fM}(\Omega_{mt}, \Omega_{ft}) > V_t^f(\Omega_{ft})$ and $V_t^{mM}(\Omega_{mt}, \Omega_{ft}) > V_t^m(\Omega_{mt})$

If the pair decides to marry they proceed to make decisions about work and fertility as described in Section III.A. If the pair decides to remain single they make decisions about work, school and (for women) fertility as described in Section III.B.

This completes the exposition of the model. As we have seen, the choice set of a married couple includes hours of work (of both partners), pregnancy and whether to stay married. Notice that we have included stochastic terms in tastes for leisure, tastes for pregnancy and utility from marriage (see equations (4), (5) and (6)). Similarly, the choice set of a single person includes hours of work, school attendance, whether to marry, and, for women, pregnancy. Again, there is a stochastic term associated with each of these decisions. Thus, there is a stochastic term associated with every choice, which guarantees that the model will produce a non-degenerate likelihood.

It is useful to discuss the mechanisms that drive marriage in the model. First, there is the public good nature of consumption for married couples. Once married, both parties consume 70.7% of total household consumption. Thus, marriage may increase consumption of both parties. Of course, marriage can also lower consumption of one party. In particular, if one party has much higher income than their potential spouse, it is likely that consumption of the former will fall after marriage. This is one factor that generates a reservation earning capacity for a potential spouse (*ceteris paribus*).

Furthermore, a person with higher earning capacity will tend to have a higher reservation earning capacity for their spouse. This occurs for two reasons: (i) the higher a person's income, the higher the income of his/her spouse must be to prevent consumption from falling after marriage, and (ii) a person with higher earning capacity will have a higher probability that his/her offers are accepted, enabling them to be more selective. These mechanisms help to generate assortative mating in the model.

A second factor that drives marriage in the model is that people get utility from marriage itself – see equation (5). But the magnitude of this utility will differ across potential spouses. This gives the individual an incentive to search over marriage offers (i.e., an option value for waiting). In equation (5) we specified that people prefer spouses with similar education. This is a direct mechanism that helps to generate assortative mating on education. Interestingly, there is a trade-off between θ_t and w_t^j (as noted earlier). This means a person is willing to accept a larger education difference if it is compensated by a higher wage.

IV. Solution of the Model

We back-solve the model from age 65 to age 17. It is important to stress that we solve the decision problem of an individual. Spouses of that individual may come and go during their lifetime, and when the person is married the couple solve the joint problem described in Section III.A. But it is the individual whose dynamic programming (DP) problem we solve. The single individual solves his/her problem understanding the probabilities of marriage and divorce, and how decisions will be made if they are married.

To discuss the solution of the DP problem it is important to list the state variables in the model. Of course, one of the individual's state variables is his/her marital status. The set of remaining state variables depends on marital status. We list all the state variables, along with the number of possible values (or grid points) for each below:

For a single person, the state variables are: Gender ($j=m, f$); Age (t), t = 16, …, 65; education (E) with 5 levels; experience (X) with a 5 level grid of 0,1-2, 3-4, 5-10, 11+; children (N) with 4 levels (0, 1, 2, 3+); health (H) with 3 levels; taste for leisure (μ_j) with 3 levels; the skill endowment (μ_j^w) with 3 levels; lagged hours (h_{t-1}) with 2 level; lagged pregnancy (p_{t-1}) with 2 levels; parents' education with 2 levels (college or not). For a single individual at age 30 the state space has 43,200 values.

For a married person, or a single person who has a marriage offer, the state variables are all of the above, plus the characteristics of the spouse or potential spouse. These are the education, experience, health, taste for leisure, skill endowment, lagged hours, and parents' education of the spouse (or potential spouse). These have the same number of possible levels as they do for the single person.[31] In addition, there is the permanent part of the match quality, or taste for marriage, (μ^M), which we assume has 3 possible levels. Note that the match quality is the same for both partners. For a married individual at age 30 the state space has roughly 700 million points.

Note that the number of children is a state variable regardless of whether the person is married. The law of motion for children conditional on a new marriage at age t is:

$$N_{t+1} = N_t + p_t - p_{t-18} + m_{t+1}(1 - m_t)N^s$$

where N^s is the number of children a spouse brings into a new marriage. Note that we do not distinguish own from spouse's children after a marriage is formed. Such a distinction is not

[31] In the case of a single person with a marriage offer, the children of the potential spouse would bring to the marriage is also relevant. We denote this by N^s and assume it has two possible levels.

possible in the data, and it would expand the state space dramatically with little benefit.

In the event of a divorce, the number of children remains a relevant state variable for both partners. It continues to enter both the $Q(\cdot)$ function in (16) and (17) and the budget constraint in (14). The differential values of A_j^s for *j* = *m*, *f* capture that men and women may have differential responsibility and/or concern for children of a prior marriage. For example, in the extreme case of $A_m^s = 0$, the male gets no utility from children of a prior marriage.

In order to reduce the burden of estimation, we rule out some choices that are fairly rare in the data. We assume there is no schooling after age 30 and no childbirth after age 40.

An important point is that, starting at age 17, a single person must make choices taking into account how they will affect his/her marriage market opportunities. This means being able to predict what the distribution of potential spouses *conditional* on own age and education will look like in *future* periods. We assume that people have perfect foresight about these distributions. This is imposed implicitly in the estimation process by: (i) using the same offer distribution that we fit within the estimation as the distribution that people use to forecast offers and (ii) requiring that the model based on this assumed distribution provides a good fit to realized assortative mating patterns. This assumption circumvents the need of to solve for the offer distribution as an endogenous object that emerges from the marriage market equilibrium, which would be infeasible in a dynamic context. Appendix A contains additional technical details about the marriage market.

V. Estimation and Identification of the Model

We estimate the model using annual data from the March CPS for the period 1964 to 2014. The sample is restricted to white civilian adults over the age of 16. We divide the entire sample into five cohorts born within two years of the reference years 1935, 1945, 1955, 1965 and 1975. For example, the 1955 cohort includes the individuals born in the years 1953-57.[32]

Dynamic discrete choice models are usually estimated using panel data. We use repeated cross-section CPS data in order to analyse the changes in household outcomes across cohorts born in the 20th century (see Eckstein and Lifshitz, 2011). We use the Method of Simulated Moments (MSM), as proposed by McFadden (1989) and Pakes and Pollard (1989), and implement it by minimizing the distance between the actual data and simulated data from our model. We estimate the parameters of the model via the Simplex algorithm.

[32] For the 1935 cohort, there is data from age 30 until 65. For the 1945 and 1955 cohorts there is data from age 16 until 61. For the 1965 there is data from age 16 to 51. For the 1975 cohort, there is data from age 16 until 41. We could not use the 1925 cohort as the data starts from age 37 and we could not use the 1985 cohort since the data exists only up to age 31. Additional sample restrictions are given in Appendix B.

The complete vector of moments that we use to fit the model are listed in Appendix C, and the complete vector of parameters is presented in Appendix D.

We simulate data from our model as follows: Conditional on the vector of parameters, which we denote θ, we numerically solve the DP problem. Given the solution, we can simulate forward to generate hypothetical life-cycle histories from age 17 until the terminal period. First, we draw initial conditions for each hypothetical person: gender, parent education, the skill type and the taste for work type.[33] Then, in order to simulate forward, we must draw, for each person i in each period t, the realization of a 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).[34] In the case of singles we draw a taste for school shock. In the case of single women and married couples we draw tastes for pregnancy. Conditional on these exogenous realizations, the model generates simulated choices and outcomes for all the observed endogenous variables: education, employment, marital status, children, wages and health.

We simulate hypothetical data for 1000 men and 1000 women for each cohort. The only difference between cohorts is in the initial conditions, which are parent education (i.e., the percentage of parents with a college degree) and the stochastic process for health. We also observe different cohorts over different age ranges. The last period of data is age 61 for the 1935, 1945 and 1955 cohorts, 51 for the 1965 cohort and 41 for the 1975 cohort. For the estimation we use the data for the cohorts of 1945, 1955 and 1965, leaving the cohorts of 1935, 1975 and 1985 as for out-of-sample prediction analysis.

For each cohort we construct a set of statistics from both the simulated and actual data that summarize key predictions of the model. The statistics include the schooling distribution by gender, employment rates of men and women conditional on age and family structure, average wages conditional on age, education and gender, marriage rates and divorce rates by age, the number of children by age and marital status, the health distribution, and the pattern of marriages by education levels of the partners. The complete set of statistics is described in detail in Appendix C. There are 1505 moments for cohorts 1945 and 1955 and 1185 moments for cohort 1965, so the model is fit to a total of 4195 moments.

Let d_j denote a statistic from the actual data, and let $d_j^s(\theta)$ be the corresponding statistic calculated from the simulated data. We then construct moments of the form:

[33] We assume that all individuals are at school at age 16 (prior to the first decision period).
[34] We first draw whether a marriage offer is received. If it is, we then draw the 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.

$$m_j^s(\theta) = \left[d_j - d_j^s(\theta)\right] \qquad \text{for} \qquad j=1,\ldots, J \text{ where } J=4195$$

The vector of simulated moments is given by $g'(\theta) = \left[m_1^s(\theta), \ldots, m_J^s(\theta)\right]$. We minimize the objective function $G(\theta) = g'(\theta)Wg(\theta)$ with respect to θ, where the weighting matrix W is a diagonal matrix consisting of the inverse of the estimated variance of each moment (from a first step).

V.A. Identification

In general, a dynamic model can be estimated from cross-sectional data, provided one observes the endogenous state variables.[35] In our case, we have the complication that experience is not observed in the CPS. For the moment we abstract from this issue, and return to it later. Given the complexity of our model, a formal analysis of identification would be extremely difficult, but here we attempt to explain the main issues:

Consider first the wage function. As wages are only observed for those who choose to work, and the wage function contains a latent variable for unobserved skill, we have selection and endogeneity bias in estimating returns to education and experience. But in our model there are several variables that affect decisions about school and work, that do not enter the wage function, and that are exogenous from the perspective of the agents. These are health, the distributions of potential partners and competitors in the marriage market, and the welfare benefit rules, $cb_t(N_t)$.

Health affects both the return to schooling and work experience in a number of ways, as it affects life expectancy and tastes for leisure. But we do not allow it to affect wages directly. The welfare benefit rules provide an obvious exclusion restriction, as they affect decisions about work, marriage and fertility but do not enter the offer wage function. Ones' marriage market opportunities conditional on education and experience are also an important source of the returns to education and experience.[36]

Interestingly, marriage market opportunities matter for the decision to leave school both through the future and the present. The quality of expected future marriage offers depends on ones' completed education level (as well as the distribution of education among other marriage market participants), so this is an important driver of education choices. But people in school also get marriage offers, and the distribution of these offers depends on their current education level.

[35] Unobserved exogenous state variables can always be integrated out of the choice probabilities, as in, for example, in Rust (1987).

[36] Completed fertility (i.e., number of children) may be correlated with skill endowment, so it is not a valid exclusion. But the arrival of newborn children shifts tastes for leisure but does not affect wages.

Given identification of the wage function, the identification of the decision rule for school attendance is rather straightforward; following, for instance, methods in Willis and Rosen (1979). A similar argument applies to the decision rules for work and marriage.

As we estimate the model using method of moments is useful to give an intuitive discussion of which moments pin down which parts of the model (although, of course, all moments may matter for all parameters). Consider first the schooling decision stage. At this point, each year agents make a choice between continuing in school, work (as they receive a wage offer each year) and unemployment. If the person leaves school and works we observe the wage. The moments involving wages conditional on zero experience, and those involving the distribution of completed schooling, pin down the parameters of tastes for schooling, as well as the effect of education on initial starting wages.[37] As the education coefficient in the wage function is age invariant, this also conveys information about returns to education.

After leaving school agents face in each year a choice of working full-time, part-time or not at all. But, given the job offer process, the person has one of three possible choice sets for hours: $D = \{0\}, \{0, 0.5\}$ or $\{0, 1\}$. We observe wages for workers. Conditional moments involving employment and wages pin down tastes for leisure and consumption, as well as parameters of the job offer function. Consider a model with a 100% job offer probability vs. a model with a lower probability. The former model would need a higher variance of tastes for leisure to generate the observed amount of unemployment (as all unemployment would have to arise from rejected offers). But the composition of who is unemployed will differ in general between the two settings (as rejection is a choice, while failing to get an offer is not).[38] Also, some parameters of the value of leisure function are pinned down by changes in employment with the arrival of a newborn.

Tastes for marriage and household economies of scale in consumption both determine marriage and divorce rates. The desirability of potential mates is determined by education and health, as well as a person specific taste shock. The degree of sorting is also determined by who one is likely to meet (equation (24)). Conditional moments involving marriage rates and marital sorting pin down these parameters. For instance, if tastes for marriage have small variance, one would choose partners solely based on income and education. More variation in tastes leads to less perfect sorting. Similarly, a lower proportion of high education types in the population reduces the probability a marrying such a type. The variation of fertility with

[37] Parents' education affects tastes for school but it also affects the probabilities of the initial skill level. So it is endogenous in the sense that it enters the wage function directly.

[38] For instance, note that we do not allow tastes for leisure to vary by education. Given this restriction, it is difficult to generate the observed unemployment among college graduates without some job destruction.

income and employment pins down parameters of the child quality production function.

Finally we turn to the issue that we do not observe respondents' work experience, only wages and age. We rely on the structure of our model to deal with this problem. Most obviously, we assume that age does not enter the wage function directly, so all wage growth over the life-cycle must be accounted for by experience. Furthermore, note that our model – in particular, the work decision rule – generates a mapping from age to experience. Many observable quantities are affected by that mapping. As one example, the magnitude of returns to work experience affects labor supply behaviour, and in particular the relationship between the wage-age profile and the wage-hours profile. Another is the observed marriage premium (in a conventional regression of wages on education, experience and a marriage dummy). Changes in the marriage premium over time may be due to changes in the age-experience mapping, as we discuss in Section VI.C.

VI. Results

VI.A. Assessing the Impact of Exogenous Factors on Life-Cycle Decisions

Our empirical strategy for assessing the impact of exogenous factors is as follows: Initially, we estimate the model on the 1945, 55 and 65 cohorts, assuming that all parameters are invariant across cohorts. We refer to this as the "benchmark model." All that differs across cohorts in this estimation are factors we assume are exogenous (i.e., mother's education and the health process). By using three cohorts in estimation, this exogenous variation in initial conditions across cohorts helps to identify the model parameters. We also use these estimates to backcast and forecast behaviour of the 1935 and 1975 cohorts, providing a partial external validation (as we explain below).[39]

As we will see, the simple baseline model is unable to explain several key behavioural differences across cohorts that we discussed in Section II (such as changes in education, labor supply, marriage/divorce rates, and fertility). Thus, our strategy is to extend the baseline model in stages, in each stage introducing a new feature that researchers in the family economics literature have hypothesized is important for explaining differences in life-cycle behaviour across these cohorts. These are: (i) changes in assortative mating, (ii) changes in divorce costs, (iii) changes in the structure of wages and job offer probabilities, and (iv) improvements in birth control technology. Our goal is to determine if we can explain most of the behavioural differences across the five cohorts using some or all of these factors, which we treat as exogenous.

[39] We do not look at earlier or later cohorts due to limited data availability.

To discipline our analysis we hold preference parameters fixed for all cohorts at their values in the baseline model. These are tastes for leisure, consumption, school, marriage, pregnancy, the quantity and quality of children, the variances of taste shocks, type differences and proportions, as well as the terminal value function. The complete set of parameters in the benchmark model is presented in Appendix D. The parameters that we allow to vary in our experiments are: (i) the marriage market matching function, (ii) divorce costs, (iii) the wage function and job offer probabilities, and (iv) the degree of randomness in pregnancy.

Stage 1: Benchmark Model. Here the only differences across cohorts are mother's education and the exogenous health transition process. In our model mother's education affects both tastes for school and the probability a person is the high ability type.[40] Table V1.1 describes the fit of the benchmark model to various key moments of interest. The columns of the table report results for each of the five cohorts. Instances where the model fit is noticeably poor are highlighted in grey.[41]

As is clear, the benchmark model provides a good fit to the behaviour of both males and females in the 1955 cohort, with the exception of slightly missing on a few aspects of the wage distribution. However, the model provides a very poor fit to all key statistics for the 1935 cohort. Several problems are also apparent for the 1945, 1965 and 1975 cohorts.

Consistent with the data, the model does generate a substantial increase in women's education across cohorts. In the data, the percentage of women with at least a college degree increases from only 9% in the 1935 cohort to 34% in the 1975 cohort. The model predicts an increase from 16% to 28%. This pattern is primarily driven by the fact that, in the model, the increase in mother's education causes women's taste for school to increase.[42] However, the model still generates too much schooling for both men and women in the 1935 cohort.

It is interesting that, despite the increase in education, the model generates no upward trend in married women's employment rate. The marriage and fertility rates do fall, but not nearly so much as in the data. And the model fails to capture changes in assortative mating patterns. Thus, while higher mother's education does increase school attendance of women, it does not have a strong impact on other life-cycle patterns. Nor do the changes in the health transition process that we also allow for here. Thus, we proceed to add additional features to the model in an attempt to better explain the observed changes in behaviour across cohorts.

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[40] The actual rates of college graduate mothers are: 6% for 1935 cohort, 6% for the 1945 cohort, 11% for the 1955 cohort and 20% for the 1965 cohort and 27% for the 1975 cohort.

[41] The criteria for what we consider a "poor" fit for each variable are listed below Table VI.1.

[42] The estimates imply the effect of mother's education on taste for school is much smaller for boys, which seems plausible. Mother's education increases the probability a person is the high ability type by the same amount for each gender, but this does not have a large impact on reported moments.

Table V1.1: Stage 1 – Benchmark Model

	1935 (out of sample)		1945		1955		1965		1975 (out of sample)	
	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
Men education distribution at 30										
HSD	0.29	0.17	0.18	0.16	0.12	0.14	0.14	0.14	0.16	0.14
HSG	0.35	0.34	0.34	0.34	0.36	0.35	0.34	0.35	0.31	0.33
SC	0.16	0.23	0.22	0.23	0.24	0.24	0.27	0.25	0.25	0.26
CG	0.15	0.18	0.17	0.19	0.20	0.19	0.19	0.18	0.20	0.19
PC	0.06	0.08	0.09	0.08	0.08	0.08	0.06	0.08	0.07	0.08
Women education distribution at 30										
HSD	0.29	0.20	0.19	0.18	0.12	0.12	0.11	0.11	0.12	0.11
HSG	0.49	0.44	0.45	0.42	0.39	0.40	0.34	0.37	0.26	0.30
SC	0.14	0.20	0.18	0.21	0.26	0.25	0.30	0.30	0.28	0.31
CG	0.08	0.13	0.15	0.16	0.19	0.19	0.20	0.18	0.24	0.21
PC	0.01	0.03	0.03	0.03	0.05	0.04	0.05	0.04	0.10	0.07
Assortative Mating										
HSD with HSD	59	54	55	54	51	54	52	54	58	54
HSG with HSG	67	58	67	58	63	58	53	56	46	56
SC with SC	25	40	34	40	43	40	48	43	49	40
CG with CG	30	40	38	40	41	42	48	42	51	42
PC with PC	10	29	22	29	30	31	33	31	45	36
HSG Women with CG Men	35	20	24	20	18	18	12	18	7	18
CG Women with HSG Men	2	8	4	8	7	8	10	8	13	9
Family moments										
Marriage Rate - Ages 25-34	0.87	0.79	0.81	0.79	0.70	0.72	0.64	0.66	0.61	0.63
Marriage Rate - Ages 35-44	0.84	0.77	0.77	0.78	0.73	0.74	0.71	0.74	0.69	0.72
Divorce Rate - Ages 25-34	0.03	0.08	0.07	0.09	0.10	0.09	0.09	0.09	0.07	0.09
Divorce Rate - Ages 35-44	0.07	0.14	0.13	0.14	0.14	0.14	0.14	0.15	0.12	0.14
Married Women # of Children - Ages 25-34	2.73	1.73	1.95	1.61	1.53	1.58	1.48	1.48	1.49	1.49
Married Women # of Children - Ages 35-44	2.24	1.89	1.96	1.89	1.80	1.89	1.87	1.88	1.94	1.96
UnMarried Women # of Children - Ages 25-34	0.97	0.35	0.43	0.35	0.34	0.33	0.35	0.29	0.36	0.27
UnMarried Women # of Children - Ages 35-44	0.67	0.51	0.55	0.51	0.49	0.51	0.50	0.50	0.53	0.49
Wages (Thousands of $)**										
Married Women - Ages 25-34	20.4	27.3	25.3	27.3	28.8	27.9	32.7	29.8	40.1	30.3
Married Women - Ages 35-44	24.4	34.6	29.9	34.6	36.8	35.0	44.8	37.5	49.3	36.6
Married Women - Ages 45-54	28.0	41.2	36.6	41.2	45.9	41.8	47.5	43.4	No Data	
Unmarried women - Ages 25-34	22.4	28.5	27.4	28.5	30.5	28.7	33.1	28.8	38.0	28.8
Unmarried women - Ages 35-44	27.9	37.0	33.0	37.0	38.3	37.1	42.4	37.2	44.0	36.3
Unmarried women - Ages 45-54	31.7	43.1	38.1	43.1	45.5	43.2	47.5	43.0	No Data	
Married Men - Ages 25-34	35.6	41.0	42.3	41.0	42.8	41.7	43.5	41.8	50.4	43.5
MarriedMen - Ages 35-44	50.8	58.8	57.1	58.8	59.4	59.5	70.9	60.0	67.8	60.3
Married Men - Ages 45-54	58.0	70.4	64.1	70.4	76.0	71.6	77.8	70.5	No Data	
Unmarried Men - Ages 25-34	30.8	34.6	36.6	34.6	37.2	34.7	37.9	35.0	41.5	34.9
Unmarried Men - Ages 35-44	40.2	46.4	48.4	46.4	44.9	46.4	49.6	46.7	53.5	45.5
Unmarried Men - Ages 45-54	49.8	53.4	53.1	53.4	54.2	53.4	54.3	53.1	No Data	
Employment****										
Married Women - Ages 25-34	0.26	0.53	0.38	0.53	0.55	0.53	0.62	0.55	0.61	0.56
Married Women - Ages 35-44	0.45	0.64	0.59	0.64	0.67	0.64	0.65	0.65	0.64	0.62
Married Women - Ages 45-54	0.53	0.70	0.66	0.70	0.70	0.70	0.67	0.71	No Data	
Unmarried women - Ages 25-34	0.68	0.74	0.72	0.74	0.75	0.73	0.74	0.74	0.74	0.74
Unmarried women - Ages 35-44	0.68	0.76	0.74	0.76	0.76	0.76	0.74	0.76	0.69	0.76
Unmarried women - Ages 45-54	0.68	0.75	0.74	0.75	0.72	0.75	0.68	0.76	No Data	
Married Men - Ages 25-34	0.93	0.92	0.91	0.92	0.88	0.91	0.89	0.91	0.89	0.92
Married Men - Ages 35-44	0.91	0.94	0.89	0.94	0.90	0.92	0.90	0.92	0.88	0.92
Married Men - Ages 45-54	0.85	0.89	0.86	0.89	0.86	0.89	0.85	0.89	No Data	
Unmarried Men - Ages 25-34	0.83	0.79	0.79	0.79	0.78	0.79	0.81	0.79	0.80	0.79
Unmarried Men - Ages 35-44	0.80	0.81	0.80	0.81	0.77	0.81	0.76	0.81	0.74	0.82
Unmarried Men - Ages 45-54	0.70	0.75	0.72	0.75	0.71	0.74	0.69	0.76	No Data	

Note: we coloured in grey cells where the gap between the predicted and the actual moment was higher than 4 percentage points

Stage 2: Matching Function. Here we allow the parameters of the marriage market matching function (equation 24) to differ across the five cohorts. The results are reported in Table VI.2A. Clearly, we now fit the patterns of assortative mating quite well for all cohorts.

Table V1.2A: Stage 2 – Matching Function Differs by Cohort

	1935 (out of sample)		1945		1955		1965		1975 (out of sample)	
	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
Men education distribution at 30										
HSD	0.29	0.17	0.18	0.17	0.12	0.14	0.14	0.15	0.16	0.14
HSG	0.35	0.34	0.34	0.34	0.36	0.35	0.34	0.35	0.31	0.31
SC	0.16	0.23	0.22	0.23	0.24	0.24	0.27	0.26	0.25	0.26
CG	0.15	0.18	0.17	0.18	0.20	0.19	0.19	0.18	0.20	0.21
PC	0.06	0.08	0.09	0.08	0.08	0.08	0.06	0.06	0.07	0.08
Women education distribution at 30										
HSD	0.29	0.18	0.19	0.18	0.12	0.12	0.11	0.11	0.12	0.11
HSG	0.49	0.44	0.45	0.44	0.39	0.40	0.34	0.35	0.26	0.25
SC	0.14	0.18	0.18	0.18	0.26	0.25	0.30	0.32	0.28	0.30
CG	0.08	0.16	0.15	0.16	0.19	0.19	0.20	0.18	0.24	0.25
PC	0.01	0.04	0.03	0.04	0.05	0.04	0.05	0.04	0.10	0.09
Assortative Mating										
HSD with HSD	59	58	55	55	51	54	52	53	58	54
HSG with HSG	67	69	67	68	63	58	53	52	46	48
SC with SC	25	28	34	32	43	40	48	49	49	52
CG with CG	30	33	38	37	41	42	48	50	51	53
PC with PC	10	15	22	29	30	31	33	32	45	41
HSG Women with CG Men	35	28	24	22	18	18	12	10	7	8
CG Women with HSG Men	2	1	4	2	7	8	10	11	13	11
Family moments										
Marriage Rate - Ages 25-34	0.87	0.82	0.81	0.80	0.70	0.71	0.64	0.66	0.61	0.63
Marriage Rate - Ages 35-44	0.84	0.81	0.77	0.78	0.73	0.74	0.71	0.74	0.69	0.72
Divorce Rate - Ages 25-34	0.03	0.08	0.07	0.09	0.10	0.09	0.09	0.09	0.07	0.09
Divorce Rate - Ages 35-44	0.07	0.14	0.13	0.14	0.14	0.14	0.14	0.15	0.12	0.14
Married Women # of Children - Ages 25-34	2.73	1.85	1.95	1.61	1.53	1.58	1.48	1.48	1.49	1.49
Married Women # of Children - Ages 35-44	2.24	1.90	1.96	1.89	1.80	1.89	1.87	1.88	1.94	1.96
UnMarried Women # of Children - Ages 25-34	0.97	0.36	0.43	0.35	0.34	0.33	0.35	0.29	0.36	0.27
UnMarried Women # of Children - Ages 35-44	0.67	0.52	0.55	0.51	0.49	0.51	0.50	0.50	0.53	0.49
Wages (Thousands of $)**										
Married Women - Ages 25-34	20.4	27.3	25.3	27.3	28.8	27.8	32.7	29.8	40.1	30.3
Married Women - Ages 35-44	24.4	34.6	29.9	34.5	36.8	35.0	44.8	37.6	49.3	36.6
Married Women - Ages 45-54	28.0	41.2	36.6	41.2	45.9	41.8	47.5	43.5	No Data	
Unmarried women - Ages 25-34	22.4	28.6	27.4	28.5	30.5	28.7	33.1	28.8	38.0	28.8
Unmarried women - Ages 35-44	27.9	37.0	33.0	37.0	38.3	37.1	42.4	37.3	44.0	36.3
Unmarried women - Ages 45-54	31.7	43.0	38.1	43.0	45.5	43.2	47.5	42.9	No Data	
Married Men - Ages 25-34	35.6	41.1	42.3	41.0	42.8	41.7	43.5	41.9	50.4	43.4
MarriedMen - Ages 35-44	50.8	58.8	57.1	58.8	59.4	59.5	70.9	60.0	67.8	60.2
Married Men - Ages 45-54	58.0	70.5	64.1	70.4	76.0	71.6	77.8	70.6	No Data	
Unmarried Men - Ages 25-34	30.8	34.6	36.6	34.6	37.2	34.6	37.9	34.9	41.5	34.9
Unmarried Men - Ages 35-44	40.2	46.4	48.4	46.4	44.9	46.4	49.6	46.7	53.5	45.5
Unmarried Men - Ages 45-54	49.8	53.3	53.1	53.4	54.2	53.4	54.3	53.1	No Data	
Employment****										
Married Women - Ages 25-34	0.26	0.53	0.38	0.54	0.55	0.54	0.62	0.55	0.61	0.56
Married Women - Ages 35-44	0.45	0.64	0.59	0.64	0.67	0.64	0.65	0.65	0.64	0.62
Married Women - Ages 45-54	0.53	0.70	0.66	0.70	0.70	0.69	0.67	0.71	No Data	
Unmarried women - Ages 25-34	0.68	0.74	0.72	0.73	0.75	0.73	0.74	0.74	0.74	0.74
Unmarried women - Ages 35-44	0.68	0.76	0.74	0.76	0.76	0.76	0.74	0.77	0.69	0.76
Unmarried women - Ages 45-54	0.68	0.75	0.74	0.75	0.72	0.75	0.68	0.76	No Data	
Married Men - Ages 25-34	0.93	0.92	0.91	0.92	0.88	0.91	0.89	0.91	0.89	0.92
Married Men - Ages 35-44	0.91	0.93	0.89	0.94	0.90	0.92	0.90	0.92	0.88	0.92
Married Men - Ages 45-54	0.85	0.89	0.86	0.89	0.86	0.88	0.85	0.89	No Data	
Unmarried Men - Ages 25-34	0.83	0.78	0.79	0.79	0.78	0.79	0.81	0.79	0.80	0.79
Unmarried Men - Ages 35-44	0.80	0.81	0.80	0.81	0.77	0.81	0.76	0.81	0.74	0.82
Unmarried Men - Ages 45-54	0.70	0.74	0.72	0.74	0.71	0.75	0.69	0.76	No Data	

For instance, in the data, the probability that a high-school woman marries a college man fell dramatically from 35% in the 1935 cohort to only 7% in the 1975 cohort. The Stage 2 model predicts a drop from 28% to 8% (slightly understating the rate for 1935). Conversely the probability that a college woman marries a high-school man increased from 2% in the 1935 cohort to 13% in the 1975 cohort. The model generates an increase from 1% to 11%.

Note that this good fit is not a forgone conclusion, as the marriage offer function does not translate directly into marriage outcomes. For example, Table VI.2B compares offer probabilities with the marriage outcome distribution. As can be clearly seen, outcomes diverge substantially from offer rates. Notice, for example, that in the 1935 cohort the probability a woman (man) with a high school (or less) education meets a college man (woman) is 11% (9%). Yet the probability of a marriage between a high-school woman (man) and a college man (woman) is 5.0% (0.3%). This is due to selection of accepted offers, which is driven by economic factors and tastes for different types of partner (see equation *). These preference parameters are held fixed across cohorts.[43,44]

Table V1.2B: Stage 2 – Marriage Offers vs. Marriage Outcomes

Women Probability 1935 (Stage 2)

W / M	HSD+HSG	SC	CG+PC
HSD+ HSG	.60	.28	.11
SC	.49	.30	.21
CG+ PC	.44	.27	.29

Men Probability 1935 (Stage 2)

M / W	HSD+HSG	SC	CG+PC
HSD+ HSG	.67	.24	.09
SC	.48	.39	.13
CG+ PC	.37	.31	.32

Assortative Mating 1935 (Stage 2)

W / M	HSD	HSG	SC	CG	PC
HSD	.099	.068	.021	.003	.001
HSG	.063	.235	.120	.050	.015
SC	.007	.034	.064	.059	.020
CG	.002	.003	.023	.059	.032
PC	.000	.000	.002	.008	.012

Women Probability 1975 (Stage 2)

W / M	HSD+HSG	SC	CG+PC
HSD+ HSG	.57	.19	.25
SC	.18	.35	.47
CG+ PC	.12	.34	.55

Men Probability 1975 (Stage 2)

M / W	HSD+HSG	SC	CG+PC
HSD+ HSG	.53	.20	.27
SC	.14	.37	.49
CG+ PC	.14	.16	.66

Assortative Mating 1975 (Stage 2)

W / M	HSD	HSG	SC	CG	PC
HSD	.076	.028	.008	.002	.000
HSG	.041	.149	.057	.017	.003
SC	.017	.093	.135	.046	.009
CG	.004	.034	.054	.111	.035
PC	.003	.006	.005	.034	.033

Despite the improved fit to marriage outcomes, the fit of the Stage 2 model to the family structure moments (i.e., marriage rate, divorce rate, number of children) does not improve noticeably from Stage 1. For the cohorts of 1935 and 1945 we continue to underestimate the marriage rate and number of children while overestimating the divorce rate, and we still fail to generate increasing employment for married women. Interestingly, the fit to the education distribution of women in the 1935 cohort actually deteriorates. The percentage of college women, already too high, increases from 16% to 20% (vs. 9% actual).

[43] To our knowledge, prior papers in the family economics literature have typically treated assortative mating outcomes as exogenous, rather than generating these outcomes from the marriage market as we do here.

[44] It is also notable how offer probabilities vary over time. For instance, for the 1935 cohort of women, the probability that a college graduate woman meets a college man is only 29%, but by the 1975 cohort it is 55%. Over the same period, the probability a college graduate man meets a college graduate woman increases from 32% to 66%.

This is because the altered matching function, which reduces the probability of meeting college men, enhances the incentives of women in the 1935 cohort to acquire education.[45]

Stage 3: Divorce Costs. In the next step, we also allow the cost of divorce to differ across the five cohorts. In the data, we can clearly see that the divorce rate was lower, and the marriage rate much higher, for the 1935 and 1945 cohorts then for later cohorts. It is well know that the earlier cohorts lived under a legal regime that made divorce more difficult.[46] It is also clear that changing social mores have reduced the psychic cost over time.

Thus, in Stage 3 we re-estimate the model allowing the divorce cost to differ between the 5 cohorts. The divorce cost parameter Δ differs by gender and presence of children. Thus, this stage generates $4 \cdot 5 = 20$ additional parameters that differ by cohort. The main change is that the estimated divorce cost becomes much higher for women in the two early cohorts. In contrast, there is little change for men (or in the impact of children).

Table VI.3 describes the fit of the Stage 3 model. As we see, the fit for the 1935 and 1945 cohorts improves substantially. For instance, in Stage 2 the divorce rate for 35-44 year olds in the 1935 cohort was predicted to be 14% vs. only 7% in the data, but now we do predict 7%. In general, the fit to divorce/marriage rates is now very precise for all cohorts.

There is also a substantial improvement in the fit to the schooling distribution. For instance, in Stage 2 we predicted that 20% of women in the 1935 cohort would obtain at least a college degree vs. only 9% in the data. But now we predict 10%. Thus, making divorce more difficult for the 1935 cohort reduces incentives for women to acquire higher education.

However, several limitations of the model are still apparent. We still substantially underestimate fertility for both married and unmarried women in the 1935 cohort, and for younger married women in the 1945 cohort. And we still fail to generate the substantial increase in the employment rate for married women over time. Interestingly, we also fail to predict the small (i.e., 3 to 4 point) decline in the employment rate of married men.

Notably, we also substantially understate the increase in wages of women over time. For instance, consider the annual wages of married women aged 35-44 conditional on employment. For the 1935 cohort this was $24.4 thousand (in 2009$), while for the 1975

[45] An interesting asymmetry is that the change in the matching function for the 1975 cohort, which increases the probability of meeting college men (conditional on one being a college woman), also enhances the incentives of women to acquire education. This improves the fit of the model, because the education of women in the 1975 cohort was slightly too low to begin with.

[46] The 1935 and 1945 cohorts lived under a mutual consent and title property regime through their early years of marriage, while the younger cohorts lived under a unilateral divorce and equal property division regime that made divorce easier, particularly for women. The legal changes occurred on a State-by-State basis, with the bulk of the change happening during the mid-1970s and early 1980s. For discussions of these changes see Matouschek and Rasul (2008), Voena (2012) and Fernández and Wong (2014).

cohort it was $49.3. In contrast, the model predicts $34.9 thousand and $36.9 thousand respectively. Interestingly, the increase in education of women, by itself, raises their wages quite modestly. Given this observation, the obvious next step is to allow for the structure of wages to change over time.

Table V1.3: Stage 3 – Divorce Cost Differs by Cohort

	1935 (out of sample)		1945		1955		1965		1975 (out of sample)	
	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
Men education distribution at 30										
HSD	0.29	0.22	0.18	0.18	0.12	0.14	0.14	0.15	0.16	0.14
HSG	0.35	0.37	0.34	0.35	0.36	0.35	0.34	0.35	0.31	0.31
SC	0.16	0.24	0.22	0.22	0.24	0.24	0.27	0.26	0.25	0.26
CG	0.15	0.11	0.17	0.17	0.20	0.19	0.19	0.18	0.20	0.21
PC	0.06	0.06	0.09	0.08	0.08	0.08	0.06	0.06	0.07	0.08
Women education distribution at 30										
HSD	0.29	0.24	0.19	0.19	0.12	0.12	0.11	0.11	0.12	0.11
HSG	0.49	0.46	0.45	0.45	0.39	0.40	0.34	0.35	0.26	0.25
SC	0.14	0.20	0.18	0.17	0.26	0.25	0.30	0.32	0.28	0.30
CG	0.08	0.08	0.15	0.16	0.19	0.19	0.20	0.18	0.24	0.25
PC	0.01	0.02	0.03	0.03	0.05	0.04	0.05	0.04	0.10	0.09
Assortative Mating										
HSD with HSD	59	58	55	54	51	54	52	53	58	54
HSG with HSG	67	69	67	68	63	58	53	52	46	48
SC with SC	25	27	34	32	43	40	48	49	49	52
CG with CG	30	34	38	37	41	42	48	50	51	53
PC with PC	10	15	22	28	30	31	33	32	45	41
HSG Women with CG Men	35	28	24	22	18	18	12	10	7	8
CG Women with HSG Men	2	1	4	2	7	8	10	11	13	11
Family moments										
Marriage Rate - Ages 25-34	0.87	0.85	0.81	0.81	0.70	0.71	0.64	0.66	0.61	0.63
Marriage Rate - Ages 35-44	0.84	0.84	0.77	0.79	0.73	0.74	0.71	0.74	0.69	0.73
Divorce Rate - Ages 25-34	0.03	0.03	0.07	0.07	0.10	0.09	0.09	0.09	0.07	0.08
Divorce Rate - Ages 35-44	0.07	0.07	0.13	0.13	0.14	0.14	0.14	0.15	0.12	0.13
Married Women # of Children - Ages 25-34	2.73	2.13	1.95	1.67	1.53	1.58	1.48	1.48	1.49	1.51
Married Women # of Children - Ages 35-44	2.24	2.10	1.96	1.90	1.80	1.89	1.87	1.88	1.94	1.98
UnMarried Women # of Children - Ages 25-34	0.97	0.36	0.43	0.35	0.34	0.33	0.35	0.29	0.36	0.28
UnMarried Women # of Children - Ages 35-44	0.67	0.52	0.55	0.51	0.49	0.51	0.50	0.50	0.53	0.50
Wages (Thousands of $)**										
Married Women - Ages 25-34	20.4	27.7	25.3	27.5	28.8	27.9	32.7	29.9	40.1	30.7
Married Women - Ages 35-44	24.4	34.9	29.9	34.8	36.8	35.1	44.8	37.6	49.3	36.9
Married Women - Ages 45-54	28.0	41.4	36.6	41.4	45.9	41.8	47.5	43.4	No Data	
Unmarried women - Ages 25-34	22.4	28.6	27.4	28.5	30.5	28.6	33.1	28.9	38.0	28.8
Unmarried women - Ages 35-44	27.9	37.1	33.0	37.1	38.3	37.1	42.4	37.2	44.0	36.3
Unmarried women - Ages 45-54	31.7	43.0	38.1	43.0	45.5	43.2	47.5	42.9	No Data	
Married Men - Ages 25-34	35.6	41.0	42.3	40.8	42.8	41.7	43.5	41.9	50.4	43.3
MarriedMen - Ages 35-44	50.8	58.5	57.1	58.5	59.4	59.4	70.9	60.1	67.8	60.1
Married Men - Ages 45-54	58.0	70.3	64.1	70.2	76.0	71.7	77.8	70.6	No Data	
Unmarried Men - Ages 25-34	30.8	34.6	36.6	34.6	37.2	34.6	37.9	34.9	41.5	34.9
Unmarried Men - Ages 35-44	40.2	46.3	48.4	46.3	44.9	46.4	49.6	46.6	53.5	45.5
Unmarried Men - Ages 45-54	49.8	53.3	53.1	53.3	54.2	53.3	54.3	53.1	No Data	
Employment****										
Married Women - Ages 25-34	0.26	0.52	0.38	0.52	0.55	0.53	0.62	0.55	0.61	0.55
Married Women - Ages 35-44	0.45	0.61	0.59	0.63	0.67	0.64	0.65	0.65	0.64	0.61
Married Women - Ages 45-54	0.53	0.67	0.66	0.69	0.70	0.69	0.67	0.71	No Data	
Unmarried women - Ages 25-34	0.68	0.73	0.72	0.73	0.75	0.73	0.74	0.74	0.74	0.73
Unmarried women - Ages 35-44	0.68	0.76	0.74	0.75	0.76	0.76	0.74	0.77	0.69	0.75
Unmarried women - Ages 45-54	0.68	0.74	0.74	0.74	0.72	0.75	0.68	0.76	No Data	
Married Men - Ages 25-34	0.93	0.94	0.91	0.92	0.88	0.91	0.89	0.91	0.89	0.93
Married Men - Ages 35-44	0.91	0.95	0.89	0.94	0.90	0.92	0.90	0.92	0.88	0.93
Married Men - Ages 45-54	0.85	0.91	0.86	0.89	0.86	0.88	0.85	0.89	No Data	
Unmarried Men - Ages 25-34	0.83	0.79	0.79	0.79	0.78	0.79	0.81	0.79	0.80	0.80
Unmarried Men - Ages 35-44	0.80	0.82	0.80	0.81	0.77	0.81	0.76	0.81	0.74	0.84
Unmarried Men - Ages 45-54	0.70	0.75	0.72	0.74	0.71	0.75	0.69	0.76	No Data	

Stage 4: Labor Market. In this stage we allow the wage offer function and the job offer probabilities to differ by cohort. When we estimate these parameters separately by cohort the results are quite interesting, so we summarize them in Table VI.4A. The left panel of the table reports the log wage function intercepts by education level, gender and cohort. A very striking pattern is the convergence of the male and female wage offer functions over time. For instance, in the 1935 cohort, the log offer wage for a woman a high school degree and no work experience is 9.32 ($11,159), while that for a comparable male is 0.61 log points higher ($20,537). And the college premium for men is 0.42 log points while that for women is only 0.29 log points. But for the 1975 cohort these differences have largely vanished.

Table VI.4.A: Wage Offer Parameters and Job Offer Probabilities by Cohort

	Return to Education Coefficients					Return to Experience		Job Offer Rates (from unemployment)			
Women	HSD	HSG	SC	CG	PC	Exp	Exp^2	HSG		CG	
								Full	Part	Full	Part
1935	9.19	9.32	9.47	9.61	9.92	0.04	-0.0002	0.33	0.34	0.34	0.37
1945	9.25	9.41	9.60	9.82	10.11	0.03	-0.0002	0.41	0.31	0.45	0.32
1955	9.24	9.43	9.64	9.91	10.24	0.04	-0.0006	0.56	0.25	0.63	0.23
1965	9.31	9.52	9.72	10.08	10.35	0.05	-0.0010	0.60	0.21	0.68	0.19
1975	9.44	9.68	9.88	10.26	10.56	0.04	-0.0012	0.60	0.20	0.68	0.17
Men											
1935	9.67	9.93	10.08	10.35	10.44	0.06	-0.0012	0.58	0.22	0.64	0.19
1945	9.80	10.11	10.26	10.45	10.59	0.04	-0.0007	0.60	0.20	0.67	0.17
1955	9.53	9.87	10.04	10.31	10.55	0.05	-0.0009	0.62	0.19	0.70	0.16
1965	9.29	9.62	9.86	10.22	10.48	0.09	-0.0020	0.65	0.17	0.74	0.12
1975	9.44	9.78	10.02	10.35	10.57	0.09	-0.0028	0.71	0.13	0.79	0.09

One obvious potential explanation for these patterns is that discrimination against women in the labor market has been greatly reduced – Jones, Manuelli and McGrattan (2003). But two other notable possibilities are that: (i) the returns to female skills may have increased, perhaps due to the growth of the service sector – see Lee and Wolpin (2006), and (ii) that human capital investments in girls prior to age 17 may have improved. Obviously our model is not designed to disentangle these scenarios.

Table VI.4A also shows job offer rates for high-school and college graduates by gender/cohort. We only report offer rates for non-employed individuals (for the employed rates are always 96 to 97%). In the 1935 cohort a non-working woman had a 1/3 chance of getting a full or part-time offer, regardless of her education level. For high-school men in the 1935 cohort the probability of a full-time offer is much higher (58%), and this increases to 68% for college men. However, the offer probabilities faced by women and men converge substantially. In the 1975 cohort, high school women are much more likely to get full-time offers (60%), and the chance is even greater for college women (68%). These figures are still below those for men (71% and 79% respectively), but the convergence is striking.

Table V1.4.B: Stage 4 – Wage Structure and Job Offers Differ by Cohort

	1935 (out of sample)		1945		1955		1965		1975 (out of sample)	
	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
Men education distribution at 30										
HSD	0.29	0.27	0.18	0.19	0.12	0.13	0.14	0.13	0.16	0.13
HSG	0.35	0.36	0.34	0.35	0.36	0.35	0.34	0.33	0.31	0.31
SC	0.16	0.18	0.22	0.21	0.24	0.24	0.27	0.27	0.25	0.26
CG	0.15	0.14	0.17	0.17	0.20	0.19	0.19	0.20	0.20	0.22
PC	0.06	0.05	0.09	0.08	0.08	0.09	0.06	0.07	0.07	0.08
AComen education distribution at 30										
HSD	0.29	0.26	0.19	0.20	0.12	0.12	0.11	0.10	0.12	0.10
HSG	0.49	0.50	0.45	0.45	0.39	0.40	0.34	0.33	0.26	0.25
SC	0.14	0.18	0.18	0.17	0.26	0.24	0.30	0.32	0.28	0.28
CG	0.08	0.06	0.15	0.15	0.19	0.19	0.20	0.19	0.24	0.26
PC	0.01	0.00	0.03	0.03	0.05	0.05	0.05	0.06	0.10	0.11
Assortative Mating										
HSD with HSD	59	58	55	56	51	54	52	54	58	56
HSG with HSG	67	66	67	68	63	60	53	52	46	48
SC with SC	25	25	34	34	43	42	48	49	49	52
CG with CG	30	33	38	39	41	43	48	50	51	53
PC with PC	10	12	22	28	30	33	33	35	45	44
HSG Women with CG Men	35	33	24	22	18	16	12	9	7	6
CG Women with HSG Men	2	2	4	2	7	8	10	11	13	12
Family moments										
Marriage Rate - Ages 25-34	0.87	0.86	0.81	0.81	0.70	0.72	0.64	0.64	0.61	0.62
Marriage Rate - Ages 35-44	0.84	0.85	0.77	0.79	0.73	0.74	0.71	0.73	0.69	0.72
Divorce Rate - Ages 25-34	0.03	0.03	0.07	0.08	0.10	0.09	0.09	0.09	0.07	0.08
Divorce Rate - Ages 35-44	0.07	0.07	0.13	0.13	0.14	0.14	0.14	0.15	0.12	0.13
Married Women # of Children - Ages 25-34	2.73	2.19	1.95	1.70	1.53	1.58	1.48	1.46	1.49	1.50
Married Women # of Children - Ages 35-44	2.24	2.11	1.96	1.92	1.80	1.89	1.87	1.85	1.94	1.97
UnMarried Women # of Children - Ages 25-34	0.97	0.34	0.43	0.34	0.34	0.33	0.35	0.29	0.36	0.28
UnMarried Women # of Children - Ages 35-44	0.67	0.49	0.55	0.50	0.49	0.51	0.50	0.50	0.53	0.50
Wages (Thousands of $)**										
Married Women - Ages 25-34	20.4	20.8	25.3	26.0	28.8	29.0	32.7	33.1	40.1	38.3
Married Women - Ages 35-44	24.4	25.3	29.9	29.9	36.8	37.8	44.8	44.5	49.3	51.1
Married Women - Ages 45-54	28.0	28.3	36.6	36.8	45.9	46.4	47.5	50.4	No Data	
Unmarried women - Ages 25-34	22.4	23.3	27.4	27.2	30.5	29.5	33.1	32.8	38.0	36.9
Unmarried women - Ages 35-44	27.9	28.7	33.0	33.1	38.3	37.7	42.4	43.7	44.0	46.5
Unmarried women - Ages 45-54	31.7	34.0	38.1	39.3	45.5	46.4	47.5	49.9	No Data	
Married Men - Ages 25-34	35.6	35.0	42.3	40.6	42.8	42.6	43.5	42.8	50.4	50.5
MarriedMen - Ages 35-44	50.8	51.2	57.1	55.5	59.4	59.6	70.9	71.1	67.8	69.1
Married Men - Ages 45-54	58.0	58.4	64.1	63.3	76.0	75.9	77.8	80.0	No Data	
Unmarried Men - Ages 25-34	30.8	29.1	36.6	37.3	37.2	37.0	37.9	36.5	41.5	42.2
Unmarried Men - Ages 35-44	40.2	42.1	48.4	48.6	44.9	45.8	49.6	51.0	53.5	54.3
Unmarried Men - Ages 45-54	49.8	51.7	53.1	54.1	54.2	54.5	54.3	56.5	No Data	
Employment****										
Married Women - Ages 25-34	0.26	0.37	0.38	0.48	0.55	0.54	0.62	0.59	0.61	0.60
Married Women - Ages 35-44	0.45	0.45	0.59	0.58	0.67	0.64	0.65	0.65	0.64	0.65
Married Women - Ages 45-54	0.53	0.53	0.66	0.66	0.70	0.70	0.67	0.73	No Data	
Unmarried women - Ages 25-34	0.68	0.68	0.72	0.72	0.75	0.74	0.74	0.74	0.74	0.74
Unmarried women - Ages 35-44	0.68	0.70	0.74	0.74	0.76	0.76	0.74	0.76	0.69	0.76
Unmarried women - Ages 45-54	0.68	0.69	0.74	0.73	0.72	0.75	0.68	0.75	No Data	
Married Men - Ages 25-34	0.93	0.90	0.91	0.88	0.88	0.88	0.89	0.88	0.89	0.89
Married Men - Ages 35-44	0.91	0.92	0.89	0.93	0.90	0.91	0.90	0.92	0.88	0.91
Married Men - Ages 45-54	0.85	0.88	0.86	0.87	0.86	0.87	0.85	0.88	No Data	
Unmarried Men - Ages 25-34	0.83	0.77	0.79	0.75	0.78	0.74	0.81	0.74	0.80	0.78
Unmarried Men - Ages 35-44	0.80	0.77	0.80	0.78	0.77	0.77	0.76	0.77	0.74	0.82
Unmarried Men - Ages 45-54	0.70	0.70	0.72	0.70	0.71	0.71	0.69	0.71	No Data	

However, there are still two key features of the data that the Stage 4 model fails to match. First, in the data, the percentage of married women aged 25 to 34 who work increases from 26% in the 1935 cohort to 61% in the 1975 cohort. Previously, we were unable to generate any substantial increase. But our Stage 4 model generates an increase from 37% to 60%. This is a great improvement, but we still predict too many young married women working in both the 1935 and 1945 cohorts (by 10 to 12 percentage points).

Second, for the 1935 cohort (and to a lesser extent the 1945 cohort) the model predicts too few children, and also misses the timing and circumstances of their birth. For instance, in the 1935 cohort, the model predicts that married women aged 25-34 have only 2.19 children, while in the data they have 2.73. Similarly, the model predicts that unmarried women aged 25-34 have only 0.34 children, while in the data they have 0.97. Thus, in the next section, we consider how to explain the very high level of childbirth (and low rate of employment) of young women in the 1935 cohort.

Stage 5: Birth Control Technology. In order to explain the high fertility and low employment of young married women in the 1935-45 cohorts, we considered explanations based on both the cost of household production (Greenwood et. al., 2012) and the use of contraception (Goldin and Katz, 2002).

First, following Greenwood et al. (2012) we tried to increase the cost of children for the early cohorts. First, we increased the parameter ρ_1 (so that women value time with children more). This closed the gap in employment but it didn't 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. [47] These results do not necessarily contradict the argument in Greenwood et al. (2012), because most of the improvements in home production technology that they emphasize had already occurred by 1950.[48]

The oral contraceptive pill was invented in the late 1950s, and approved by the FDA in 1960. It became available to married women in all states after *Griswold v. Connecticut*, 1965, and to unmarried women in all states after *Eisenstadt v. Baird,* 1972. Thus, in our data, oral contraceptives were not available to the 1935 cohort until late in their reproductive years, while availability to the 1945 was mixed. But the 1955-75 cohorts had unrestrictive access to oral contraception. Goldin and Katz (2002) argue that the oral contraceptive pill was a key driver of reduced fertility and increased education/employment among women.

As oral contraceptives were unavailable (or restricted) for women in the 1935 and 1945 cohorts, we alter the model to generate unplanned pregnancies for these cohorts only.

[47] Eckstein and Lifshitz (2011) find 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.

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

Specifically, we add a *positive* shock to equation (6), which we denote by ε_t^{up}. This shock

Table V1.5: Stage 5 – Full Model – Birth Control Differs by Cohort

	1935 (out of sample)		1945		1955		1965		1975 (out of sample)	
	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
Men education distribution at 30										
HSD	0.29	0.28	0.18	0.19	0.12	0.13	0.14	0.13	0.16	0.13
HSG	0.35	0.36	0.34	0.35	0.36	0.35	0.34	0.33	0.31	0.31
SC	0.16	0.17	0.22	0.21	0.24	0.24	0.27	0.27	0.25	0.26
CG	0.15	0.14	0.17	0.17	0.20	0.19	0.19	0.20	0.20	0.22
PC	0.06	0.05	0.09	0.08	0.08	0.09	0.06	0.07	0.07	0.08
AComen education distribution at 30										
HSD	0.29	0.28	0.19	0.20	0.12	0.12	0.11	0.10	0.12	0.10
HSG	0.49	0.50	0.45	0.46	0.39	0.40	0.34	0.33	0.26	0.25
SC	0.14	0.16	0.18	0.18	0.26	0.24	0.30	0.32	0.28	0.28
CG	0.08	0.06	0.15	0.14	0.19	0.19	0.20	0.19	0.24	0.26
PC	0.01	0.00	0.03	0.02	0.05	0.05	0.05	0.06	0.10	0.11
Assortative Mating										
HSD with HSD	59	57	55	55	51	54	52	54	58	56
HSG with HSG	67	66	67	68	63	60	53	52	46	48
SC with SC	25	25	34	34	43	42	48	49	49	52
CG with CG	30	32	38	39	41	43	48	50	51	53
PC with PC	10	11	22	27	30	33	33	35	45	44
HSG Women with CG Men	35	34	24	22	18	16	12	9	7	6
CG Women with HSG Men	2	2	4	3	7	8	10	11	13	12
Family moments										
Marriage Rate - Ages 25-34	0.87	0.86	0.81	0.81	0.70	0.72	0.64	0.64	0.61	0.62
Marriage Rate - Ages 35-44	0.84	0.84	0.77	0.79	0.73	0.74	0.71	0.73	0.69	0.72
Divorce Rate - Ages 25-34	0.03	0.02	0.07	0.06	0.10	0.09	0.09	0.09	0.07	0.08
Divorce Rate - Ages 35-44	0.07	0.07	0.13	0.12	0.14	0.14	0.14	0.15	0.12	0.13
Married Women # of Children - Ages 25-34	2.73	2.69	1.95	1.86	1.53	1.58	1.48	1.46	1.49	1.50
Married Women # of Children - Ages 35-44	2.24	2.36	1.96	2.02	1.80	1.89	1.87	1.85	1.94	1.97
UnMarried Women # of Children - Ages 25-34	0.97	0.91	0.43	0.45	0.34	0.33	0.35	0.29	0.36	0.28
UnMarried Women # of Children - Ages 35-44	0.67	0.78	0.55	0.58	0.49	0.51	0.50	0.50	0.53	0.50
Wages (Thousands of $)**										
Married Women - Ages 25-34	20.4	21.2	25.3	26.4	28.8	29.0	32.7	33.1	40.1	38.3
Married Women - Ages 35-44	24.4	25.6	29.9	30.3	36.8	37.8	44.8	44.5	49.3	51.1
Married Women - Ages 45-54	28.0	28.9	36.6	37.1	45.9	46.4	47.5	50.4	No Data	
Unmarried women - Ages 25-34	22.4	22.6	27.4	26.5	30.5	29.5	33.1	32.8	38.0	36.9
Unmarried women - Ages 35-44	27.9	27.8	33.0	32.6	38.3	37.7	42.4	43.7	44.0	46.5
Unmarried women - Ages 45-54	31.7	32.8	38.1	38.7	45.5	46.4	47.5	49.9	No Data	
Married Men - Ages 25-34	35.6	35.5	42.3	41.2	42.8	42.6	43.5	42.8	50.4	50.5
MarriedMen - Ages 35-44	50.8	51.5	57.1	56.0	59.4	59.6	70.9	71.1	67.8	69.1
Married Men - Ages 45-54	58.0	58.8	64.1	64.0	76.0	75.9	77.8	80.0	No Data	
Unmarried Men - Ages 25-34	30.8	29.3	36.6	37.1	37.2	37.0	37.9	36.5	41.5	42.2
Unmarried Men - Ages 35-44	40.2	42.1	48.4	48.5	44.9	45.8	49.6	51.0	53.5	54.3
Unmarried Men - Ages 45-54	49.8	51.9	53.1	54.0	54.2	54.5	54.3	56.5	No Data	
Employment****										
Married Women - Ages 25-34	0.26	0.29	0.38	0.38	0.55	0.54	0.62	0.59	0.61	0.60
Married Women - Ages 35-44	0.45	0.43	0.59	0.55	0.67	0.64	0.65	0.65	0.64	0.65
Married Women - Ages 45-54	0.53	0.53	0.66	0.66	0.70	0.70	0.67	0.73	No Data	
Unmarried women - Ages 25-34	0.68	0.66	0.72	0.70	0.75	0.74	0.74	0.74	0.74	0.74
Unmarried women - Ages 35-44	0.68	0.69	0.74	0.74	0.76	0.76	0.74	0.76	0.69	0.76
Unmarried women - Ages 45-54	0.68	0.69	0.74	0.73	0.72	0.75	0.68	0.75	No Data	
Married Men - Ages 25-34	0.93	0.92	0.91	0.90	0.88	0.88	0.89	0.88	0.89	0.89
Married Men - Ages 35-44	0.91	0.94	0.89	0.92	0.90	0.91	0.90	0.92	0.88	0.91
Married Men - Ages 45-54	0.85	0.89	0.86	0.89	0.86	0.87	0.85	0.88	No Data	
Unmarried Men - Ages 25-34	0.83	0.77	0.79	0.75	0.78	0.74	0.81	0.74	0.80	0.78
Unmarried Men - Ages 35-44	0.80	0.78	0.80	0.78	0.77	0.77	0.76	0.77	0.74	0.82
Unmarried Men - Ages 45-54	0.70	0.71	0.72	0.70	0.71	0.71	0.69	0.71	No Data	

generates unexpected jumps in utility from pregnancy, an event observationally equivalent in our model to random failures of contraception. We then re-estimate the model for the first two cohorts. For the 1935 cohort, we obtain $\varepsilon_t^{up} \sim iidN(-0.18,1)$, while for the 1945 cohort we obtain $\varepsilon_t^{up} \sim iidN(-0.79,1)$. These estimates are consistent with the idea that fertility control was *much* more difficult for the 1935 cohort, because they did not have access to oral contraception, and *somewhat* more difficult for the 1945 cohort, who had limited access.

The results from our complete model specification are presented in Table VI.5. As one can see from the lack of grey shading, our complete Stage 5 model matches nearly all key moments for all five cohorts quite accurately. The introduction of positive fertility shocks for the early cohorts has two key effects: First, it increases fertility for both married and single women, bringing the model predictions closely into line with the data. For the 1935 cohort, who had no access to oral contraception at all, the increases in fertility are very dramatic – e.g., from 0.34 to 0.91 children on average for single women aged 25 to 34. Second, it reduces employment of married women aged 25 to 35 by roughly 10 percentage points, also bringing it closely in line with the data.

Interestingly, while our results support the idea that availability of contraception was a key factor leading to reduced fertility and increased employment of women, we also find that the reduction of "unintended" pregnancy via availability of the pill has little effect on education – i.e., the education distribution is little changed between Stages 4 and 5.

VI.B. Decomposing the Sources of Differences between the 1935 and 1975 Cohorts

We now turn to a summary of how each factor contributed to changes in behaviour between the 1935 and 1975 cohorts.[49] The results are presented in Table VI.6. For instance, the percentage of women who are at least college graduates increased from 6% to 37%, an increase of 517%. According to our model, the key factors driving this increase were increased mother's education (stage 1), lower divorce costs (stage 3), and better labor market prospects for women (stage 4). In contrast, we estimate that the improved availability of contraception (stage 5) had essentially no effect.

The college graduation rate of men rose much less than that of women (58%). Much of this increase is attributable to changes in divorce laws. Divorce has negative economic consequences for men just as for women, as they both lose the economies of scale in home production that arise from marriage. Thus, if divorce becomes less costly then both genders have an incentive to acquire more education to insure against increased divorce risk.

The marriage rate for 25-34 year olds fell by 28% from the 1935 to 1975 cohorts, while that for 35-44 year olds fell by 15%. Together, these statistics imply that marriage is being delayed. This implies that increased mother's education, which, as we have seen, has

[49] Since the main changes in demographics are monotonic across cohorts (or nearly so), we felt it would not add much to look at the intermediate cohort.

the primary effect of increasing women's education, is the main factor driving the reduction of marriage at early ages. It accounts for 19%, or about 2/3, of the drop. In contrast, no single factor explains most of the drop in marriage at older ages.

Table VI.6: Decomposing Sources of Cohort Differences

	1935 Fitted	1975 Fitted	Total % Change	Stage 1: Benchmark Model	Stage 2: Marriage offer	Stage 3: Divorce Cost	Stage 4: Wage and Job Offer	Stage 5: Fertility Shocks
Men education distribution at 30								
CG+PC	0.19	0.30	58%	5%	11%	47%	-5%	0%
Women education distribution at 30								
CG+PC	0.06	0.37	517%	200%	33%	167%	117%	0%
Family moments								
Marriage Rate - Ages 25-34	0.86	0.62	-28%	-19%	-3%	-4%	-2%	0%
Marriage Rate - Ages 35-44	0.84	0.72	-15%	-6%	-4%	-2%	-3%	1%
Divorce Rate - Ages 25-34	0.02	0.08	302%	48%	-13%	209%	-4%	61%
Divorce Rate - Ages 35-44	0.07	0.13	85%	3%	-2%	88%	-4%	-1%
Married Women # of Children - Ages 25-34	2.69	1.50	-44%	-9%	-4%	-10%	-3%	-18%
Married Women # of Children - Ages 35-44	2.36	1.97	-17%	-3%	1%	-3%	-1%	-11%
UnMarried Women # of Children - Ages 25-34	0.91	0.28	-69%	-9%	-2%	1%	3%	-63%
UnMarried Women # of Children - Ages 35-44	0.78	0.50	-36%	-2%	-1%	1%	2%	-35%
Wages (Thousands of $)								
Married Women - Ages 25-34	21.2	38.3	81%	14%	0%	0%	68%	-2%
Married Women - Ages 35-44	25.6	51.1	100%	8%	0%	0%	93%	-1%
Employment								
Married Women - Ages 25-34	0.29	0.60	110%	10%	0%	1%	67%	31%
Married Women - Ages 35-44	0.43	0.65	52%	4%	-1%	-2%	46%	4%

The divorce rate increased by a massive 302% at ages 25-34, and by a more modest 85% at ages 35-44. Still, even for the 1975 cohort, the divorce rate remained higher for the older age group (13% vs. 8%). Interestingly, the model implies that at older ages the increase in the divorce rate was almost entirely due to the reduction in divorce costs. But at younger ages increased women's education and availability of contraception also play important roles.

The average number of children for married women aged 35-44 fell by 17%. About 2/3 of this drop was due to the availability of oral contraception. The rest is split between higher education and lower divorce costs. For younger married women (25-34) the drop is much more substantial (44%), indicative of delays in fertility. Contraception still explains a large part of this drop, but the majority (60%) is explained by economic factors: higher women's education, lower divorce costs, higher female wage offers and changes in marriage market conditions. Thus, it appears that contraception explains most of the drop in *completed* fertility for married women, but economic factors explain most of the *delay* in fertility.

Fertility of unmarried women fell much more sharply than that of married women. Strikingly, the model implies that the large drop in children for unwed women was almost entirely due to the availability of oral contraception. Viewed another way, the model implies that most births to unwed mothers are unplanned (i.e., induced by the ε_t^{up} shocks).

The wages of (employed) married women increased substantially (81% at ages 25-34, 100% at ages 35-44). The model implies that only a small fraction of this increase was due to increased women's education (no more than 17%). As we have seen, returns to education were much smaller for women than for men in the 1935 cohort. Most of the increase in women's wages was due to changes in the wage structure that increased their relative wages at all levels of education, and that increased their returns to education. By the 1975 cohort the wage structure for women was quite similar to that for men.

Finally, the employment rate of married women aged 25-34 increased by 110% over this period. Strikingly, the model implies that roughly 2/3 of this increase was due to changes in the wage/employment structure while about 1/3 was due to oral contraception.[50] In contrast, at ages 35-44, the increase is half as large (52%) and the model implies it is almost entirely due the changing wage structure. It is intuitive that oral contraception had a much greater effect on the employment decisions of younger women.

VI.C. The Marriage Premium

As we noted in Section II, there were substantial changes in marital sorting over the 1962-2012 period, both in terms of observables and unobservables. The level of education of married women rose substantially relative to both single women and married men. And the so-called "marriage wage premium" for women rose substantially. Recall that the marriage premium is defined as the coefficient on marriage in a standard Mincer earnings equation of log wages on education, age and age squared.

There are two key reasons that the marriage premium may change over time: changes in the nature of selection into marriage, and changes in human capital investment of married vs. single women. Consider first selection into marriage. The relative "quality" of married women in terms of their position in the distribution of unobserved ability may have improved over time. That is, in the 1935 cohort there may have been a tendency for high ability women to stay single, but in the 1975 cohort the high ability women were more likely to marry.

The second possibility is that the rate of investment in human capital by married women may have increased over time. The Mincer equation conditions on age, but it is actually work experience that determines human capital. Part of the marriage premium may simply reflect the fact that married women have less work experience per year of age than

[50] In addition, only a small part of the increase in women's work was due to the increase in mother's education, as we discussed earlier.

single women. But the mapping from age to work experience shifted substantially over time: In the 1935 cohort married women worked much less than single women, but by the 1965 cohort they work nearly as much. This change would cause the marriage premium to decline.

Note that the marriage premium is not a moment to which our model was fit. Thus, our ability to fit the marriage premium is a test of the external validity of the model.

To proceed, we estimated Mincer equations on each cohort of women, using both the actual CPS data and simulated data from our models. By running separate regressions for each of our models from Stages 1 to 5, we can assess how much different factors contribute to explaining changes in the marriage premium. Table VI.7 reports the results.

Table VI.7: Marriage Premium for Women

	Women Marriage Premium				
	1935	1945	1955	1965	1975
Data	-10.40%	-7.65%	-1.46%	3.25%	6.79%
Stage 1: Benchmark Model	-3.85%	-3.79%	-0.97%	0.59%	1.14%
Stage 2: Marriage offer	-3.91%	-3.84%	-0.98%	0.52%	1.13%
Stage 3: Divorce Cost	-5.06%	-4.30%	-0.97%	0.60%	1.34%
Stage 4: Wage and Job Offer	-7.85%	-6.13%	-1.05%	2.48%	4.73%
Stage 5: Fertility Shocks	-8.40%	-6.53%	-1.05%	2.48%	4.73%
Control for Experience	-3.26%	-2.60%	2.24%	4.35%	5.59%
Control for Ability	1.20%	0.91%	1.55%	0.28%	2.20%

In the data we see the striking result that the marriage premium shifts from -10.4% in the 1935 cohort to 6.8% in the 1975 cohort. This is a 17.2 percentage point increase in the marriage premium. The implication is that in the 1935 cohort married women tended to be below single women in terms of their level of unobserved labor market skills. But for the 1975 cohort this pattern of "negative" selection into marriage is reversed and we instead have "positive" selection.

The 2^{nd} row of table VI.7 presents the marriage premium for the benchmark model. Here only mother's education and the health transition matrix differ across cohorts. As we saw earlier, this has the principle effect of causing women's education to increase across cohorts, while having little effect on other outcomes. As we see in Table VI.7, simulated data from the Stage 1 model does generate a modest 5 percentage point increase in the marriage premium from the 1935 cohort to the 1975 cohort – roughly 30% of the observed increase.

Account for changes in the marriage offer distribution and the cost of divorce (Stages 2 and 3) leads to only a small increase in the part of the marriage premium that the model can explain. Once we include changes in the wage and job offers (Stage 4) the model predicts a 12.6 percentage point increase in the marriage premium, which is 73% of the observed increase. Our full model (Stage 5), which also includes accounts for availability of contraception, increases this only marginally to 13.1 points or 76%.

Recall that our analysis is disciplined by the assumed that preferences are invariant across cohorts. The remaining 24% of the change of the marriage premium that we do not explain could be due to changing preferences. For example, taste for marriage to a person of similar (unobserved) skill level may have varied over time. Of course, other exogenous changes that we have failed to account for may also explain the residual change in the marriage premium.

In the row of Table VI.7 labelled "control for experience" we take the simulated data from the Stage 5 model and include true work experience rather than age in the Mincer equation. Of course this is only possible in the simulated data because we only observe age in the CPS data. With this change the model predicts an 8.9 percentage point increase in the marriage premium. Thus the model implies that 13.1 – 8.9 = 4.2 points (or one-third) of the predicted increase in the marriage premium is due to changes in the mapping from age to experience (i.e., married women working more).

Finally. in the last column of Table VI.7, we also control for unobserved ability, which of course we can observe in the simulated data. In principle, if the mapping from education, experience, experience-squared and latent ability to wages was exactly log linear, then this equation should control for all differences between married and single women, and the marriage premium should vanish. In fact, the equation implies a small (but statistically insignificant) positive marriage premium for all cohorts, that increases by exactly one percentage point. Thus, we find that 8.9 – 1.0 = 7.9 percentage points or 60% of the increase of the marriage premium is due to selection of higher ability women into marriage.[51] Overall, our model is able to explain roughly ¾ of the increase in the women's marriage wage premium.

Another feature of the data that we discussed in Section II is that the wage premium for married men declined over our sample period. Thus, we repeated the same analysis for married men. The results are presented in Table VI.8.

[51] The residual 1 point that is unaccounted for is presumably due to misspecification of the functional form of the wage function. For example, the correct conditional expectation function may include higher order terms in education or experience, interactions between education and experience, interactions between ability and experience, etc. However, it would appear that biases due to such misspecifications are minor, as marriage premium in simulated data regressions that include both latent ability and experience are very small.

Table VI.8: Marriage Premium for Men

	Men Marriage Premium				
	1935	1945	1955	1965	1975
Data	19.70%	18.50%	19.40%	17.80%	16.90%
Stage 1: Benchmark Model	11.11%	11.12%	11.64%	11.89%	11.86%
Stage 2: Marriage offer	11.13%	11.11%	11.64%	11.84%	11.81%
Stage 3: Divorce Cost	10.87%	10.84%	11.67%	11.90%	11.82%
Stage 4: Wage and Job Offer	12.90%	13.25%	12.91%	13.11%	13.20%
Stage 5: Fertility Shocks	12.50%	13.10%	12.91%	13.11%	13.20%
Control for Experience	4.70%	4.91%	5.79%	6.91%	7.18%
Control for Ability	-0.50%	0.90%	0.94%	0.96%	1.53%

In the data, the marriage premium for men dropped by 2.8 percentage points from the 1935 cohort to the 1975 cohort. But our model fails to generate any significant change in the marriage premium for men across cohorts. However, given that the change was very modest (particularly compared to the large change for women), the real issue for men is to explain the absolute level of the marriage premium, which is large for all cohorts (i.e., roughly 17% to 20%). Our full model (Stage 5) generates a marriage premium of roughly 13% for all cohorts. Thus, our model generates roughly 2/3 to ¾ of the marriage premium for men.

If we take simulated data from our full model (Stage 5) and run the Mincer regression substituting true experience for age, the marriage premium for men drops to about 5 to 7%. Thus, the model implies that roughly half of the marriage premium for men is explained by married men accumulating more work experience per unit of age (i.e., married men "working harder"). If we also control for latent ability, the marriage premium for men becomes small and insignificant. Thus, the remaining half of the marriage premium is explained by selection into marriage of men with higher unobserved ability.[52]

It is interesting that the benchmark model (Stage 1) generates a marriage premium of roughly 11 to 12% for all cohorts, which is well over half of the marriage premium for men, and nearly as large as in generated by the full model. In contrast, as we saw in Table VI.7, the benchmark model can only generate a small fraction of the marriage premium for women. This suggests that the additional factors that we add in stages 2 to 5 (i.e., changes in the marriage offer distribution, divorce laws, the wage offer distribution and availability of contraception) had a large effect on selection of women into marriage (based on unobserved skills), but had little effect on the selection of men into marriage.

[52] Recall from equation (25) that the marriage offer for a single woman includes the latent variables μ_m^l, μ_m^W that capture the man's taste for leisure and skill endowment. The analogous terms are part of the marriage offer received by single males. Also recall that in our model we assume that these latent attributes are observed by both parties prior to the decision of whether to form the marriage.

VI.D. Selection Bias in the Women's Wage Equation

Finally, we ask how conventional Mincer wage equation estimates compare to the structural wage function estimates from our model. Recall that structural estimates for each cohort were given in Table VI.4.A. We present the Mincer equation estimates for each cohort in the CPS in Table VI.9. In the structural model wages depend on actual work experience, but in the Mincer equation we use "potential experience" (i.e., age – education), as actual experience is not observed in the data. We estimate the Mincer equation with and without a marriage dummy (of course, this is not included in the structural wage equation).

The most striking contrast in the results is that the Mincer equation estimates imply essentially no returns to experience for women in the 1935 and 1945 cohorts. For the later cohorts the Mincer estimates of returns to experience rise to about 3% to 4% per year (when evaluated at X_t=0). In contrast, the structural estimates imply that returns to experience were quite stable at roughly 4% per year across all cohorts (see Table VI.4.A). The Mincer estimates of experience returns approach the structural estimates over time because for later cohorts "potential experience" is a better proxy for actual experience. We also see that controlling for marital status slightly increases the Mincer experience returns.[53]

Table VI.9: Women's Mincer Regression Coefficients (Marriage Premium Bias)

	Women's Return to Education Coefficients										Women's Return to Experience			
	HSD		HSG		SC		CG		PC		Exp		Exp^2	
	no M	with M	no M	with M	no M	with M	no M	with M	no M	with M	no M	with M	no M	with M
1935	9.17	9.38	9.37	9.59	9.52	9.72	9.72	9.93	10.18	10.35	0.01	0.01	0.0000	-0.0001
1945	9.23	9.39	9.49	9.66	9.73	9.89	9.96	10.12	10.31	10.46	0.00	0.01	0.0003	0.0003
1955	9.12	9.19	9.46	9.54	9.70	9.78	9.99	10.07	10.31	10.39	0.02	0.03	-0.0001	-0.0001
1965	9.20	9.23	9.52	9.55	9.74	9.77	10.10	10.14	10.40	10.44	0.03	0.04	-0.0005	-0.0006
1975	9.32	9.33	9.64	9.65	9.85	9.86	10.25	10.26	10.54	10.55	0.03	0.04	-0.0010	-0.0010

Turning to education, results in Table VI.4.A indicate that the college vs. high school wage premium for women went from 0.29 log points in the 1935 cohort to 0.58 log points in the 1975 cohort. Similarly, in Table VI.9, the Mincer estimate of the college wage premium goes from 0.35 log points in the 1935 cohort to 0.61 log points in the 1975 cohort (whether one controls for marital status makes little difference). So in each case we see the dramatic increase in returns to education for women that we noted in Section VI.A. Unlike experience returns, there is little evidence of selection bias in the Mincer estimates of either the levels or changes in returns to education.

[53] As we already saw in Section VI.C, one reason marital status is significant in Mincer equations is that it is correlated with the difference between true and "potential" experience. So controlling for marital status slightly mitigates the downward bias in the Mincer experience return estimates.

VII. Conclusion

We have studied the life-cycle decisions of five cohorts of American men and women born from the 1930s to the 1970s. Comparing the 1935 to 1975 cohorts, we see dramatic socio-economic changes, such as greatly increased employment for married women – against a backdrop of great stability in the employment patterns of both men and single women. Using a life-cycle model that incorporates both individual and household decision making, as well as the interaction of men and women in the marriage market, we show that we can almost fully explain the major observed changes in behavior across cohorts via five exogenous factors: parental education, the distribution of potential partners, divorce laws, the wage offer distribution, and birth control technology:

Mothers' Education. Our model implies that the increase in mothers' education across cohorts had the primary impact of increasing women's tastes for school. This explains 40% of their increase in education.[54] It also explains 1/6 of the increase in the divorce rate.

Distribution of Partners. The increase in education that occurs across cohorts translates into changes in marriage offer probabilities. Interestingly, we find that this leads to only modest changes in outcomes, other than the pattern of assortative mating by education itself. For instance, it can account for only 6% of the increase in women's education.

Divorce Laws. Legal changes over the period led to lower divorce costs for women. This accounts for 2/3 of the increase in the divorce rate for those under 35 and all of the increase for those over 35. It can also account of 1/3 of the increase in women's education.

Wage and Job Offers. Across the five cohorts the wage and job offer distributions of women shifted to become much closer to those for men. These changes accounted for 20% of the increase in women's education, nearly 2/3 of the increase in employment for married women aged 25 to 34, and almost all of the increase in employment for married women aged 35 to 44. Changes in the structure of wages and job offers are also the single biggest factor that drove the shift in selection of women into marriage from "negative" selection on ability in the 1935 cohort to "positive" selection in the 1975 cohort.

Birth Control. Our model implies that the availability of oral contraceptives accounts for 40% of the drop in children for married women aged 25-34, about 2/3 of the drop for married women aged 35-44, and essentially all of the sharp drop in children for single women of all ages. Birth control also accounts for about 30% of the dramatic increase of employment among married women aged 25-34. And it explains 20% of the increase in the divorce rate.

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[54] To discipline the analysis we assume that preferences are invariant over cohorts. This means that the taste for school <u>conditional</u> on parent education is invariant.

In summary, we see that no one factor can explain the multiplicity of socio-economic changes that we observe over the past 50 years. All five factors we have considered are important in one or more dimensions. One interesting implication of our results is that the increase in women's education did not, by itself, lead to much improvement in their labor market prospects. Only after women's returns to education began to catch up to those of men did higher education translate in higher wages and employment.

In addition to these substantive results, we also make a number of methodological innovations. Our model can be viewed as combining the life-cycle models of Keane and Wolpin (1997, 2010), that model men and women separately, into a unified framework of individuals and family decisions following the cooperative model, as in Chiappori (1988, 1992) and Mazzocco et. at. (2007). Many features of our framework have been implemented separately in prior work such as Greenwood et al (2012) and Fernández and Wong (2011). But we integrate several features that have not previously been included in one empirical model: endogenous education, the marriage market, endogenous individual and household labor supply, endogenous fertility, endogenous wages, etc.. We present a new way of modelling how children affect tastes for leisure that makes the structural modelling of fertility much easier. And we present some innovative techniques to simplify the problem of solving a marriage market model in a dynamic context. Finally, a novel feature of the paper is that we use repeated cross section data from multiple cohorts to estimate a dynamic model.

There are a number of potential extensions of the paper. First, it would be interesting to look at data from earlier cohorts. There is a literature that finds an important role for improvements in home production technology in increasing women's labor supply (e.g., Greenwood et al (2005)). But these innovations were widely diffused by the time of the 1935 cohort, who reach age 17 in 1952. We need to look at earlier cohorts to assess the importance of home technology innovations.

Second, an important motivation for modelling the marriage market is to understand the labor supply of couples. We can use our model to simulate effects of taxes on the labor supply of both individuals and couples, accounting for endogenous family formation. Of particular interest would be to look at the impact of the so-called "marriage tax." [55]

Third, it would be interesting to look at the implications of our model for changes in inequality. Did changes in assortative mating lead to increased inequality across households?

[55] Apps and Rees (2009) emphasize the importance of modelling joint labor supply decisions of couples in order to understand the impact of taxes on labor supply and welfare. The existing literature on joint labor supply of couples is essentially static, treating marital sorting, fertility and human capital as exogenously given.

Finally, we can use our model to forecast changes in the socio-demographic structure into the future. What links generations in our model is education: The educational attainment of parents affects the preference and skill distributions of their children. We can use the educational distribution generated by our model for the 1965 cohort to generate initial conditions for the 1985 cohort, and so on.[56] We can then see if the model predicts that variables like women's employment rate, the marriage rate and the divorce rate will continue to change, or whether they will stabilize. Investigation of the 1965 and 1975 cohorts gives a preliminary indication that stabilization has already occurred, but we need to look further ahead to have confidence in this conclusion.

[56] An important point is that our model fits the distribution of completed education very well for every cohort. This means that, while each cohort treats their parents' education as exogenous (or predetermined), our model is successful in explaining the evolution of the education distribution across the 1935 to 1975 cohorts.

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Appendix A: Technical notes on 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 – i.e., 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.[57] 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 – i.e., 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 <u>infinite</u> 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,…,*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 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

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

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.

Appendix B: Data notes

Data was 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 work experience in the United States. A detailed description of the survey can be found at: www.bls.census.gov/cps/ads/adsmain.htm.

Our data, for the years 1962-2014, was extracted using the IPUMS.

The sample is restricted to white civilian adults, ignoring armed forces and children. 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.

Wages are multiplied by 1.75 for top-coded observations until 1995. Nominal wages are deflated using the Personal Consumption Expenditure (PCE) index from NIPA Table 2.3.4 (http://www.bea.gov/national/nipaweb/index.asp). Since wages refer to the previous year, we use PCE for year t-1 for observations in year t and therefore all wages are expressed in constant 2009 dollars.

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. 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).

Table B.1: Descriptive statistics

Cohort	Obs.	Obs. Per Year	% of college graduate mothers
1935	230,936	5633	6%
1945	381,075	7472	6%
1955	483,141	10503	11%
1965	380,927	10581	20%
1975	217,019	8347	27%

The welfare payment by number of children for single mothers is given by the function $cb_t(N_t) \cdot I(j = f, N_t > 0)$ as in equation (13). It is estimated separately using the data on welfare from the CPS which is captured by the variable INCWELFR in IPUMS. This variable 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 the effects of inflation using PCE (personal consumption expenditure) deflators - NIPA Table 2.3.4, as we did with all wages in our sample.

We then run a regression of the real annual welfare payment as a function of the number of children for non-married, unemployed women with children who get welfare benefits. We run the regression on different cohorts and different years and over all the result were similar (there is a decrease in the welfare benefit for the year 1993 and after). The regression results are given Table B.2. Based on the results we use the following scale of for annual welfare payments for single mothers (2009 prices): For one child 4700 dollars and 1100 dollars for each additional child.

Table B.2: Welfare payments as function of children

```
. reg  real_welfare  child18 if  marstat!=1 &  real_welfare>0 &  emp_stat>2 & child18 >0 & child18 !=.

      Source |       SS       df       MS              Number of obs =   42350
-------------+------------------------------           F(  1, 42348) = 6476.36
       Model |  9.5943e+10     1  9.5943e+10           Prob > F      =  0.0000
    Residual |  6.2736e+11 42348  14814346.3           R-squared     =  0.1326
-------------+------------------------------           Adj R-squared =  0.1326
       Total |  7.2330e+11 42349  17079529.8           Root MSE      =  3848.9

------------------------------------------------------------------------------
real_welfare |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     child18 |   1087.297   13.51084    80.48   0.000     1060.815    1113.778
       _cons |   3641.214   36.46489    99.86   0.000     3569.742    3712.686
------------------------------------------------------------------------------
```

Appendix C: Moments

The moments for stage 1 are listed below. There are 1505 moments for each of the cohorts of 1945 and 1955 and 1185 moments for the cohort of 1965 as follows:

Moment	# of moments 1945	# of moments 1955	# of moments 1965
Married Women Full Time	40*	40*	30**
Unmarried Women Full Time	40*	40*	30**
Married Men Full Time	40*	40*	30**
Unmarried Men Full Time	40*	40*	30**
Married Women Part Time	40*	40*	30**
Unmarried Women Part Time	40*	40*	30**
Married Men Part Time	40*	40*	30**
Unmarried Men Part Time	40*	40*	30**
Married with Children Women Employment	40*	40*	30**
Married no Children Women Employment	40*	40*	30**
Unmarried with Children Women Employment	40*	40*	30**
Unmarried no Children Women Employment	40*	40*	30**
Men Schooling Distribution – 5 groups	4 X 14***	4 X 14***	4 X 14***
Women Schooling Distribution – 5 groups	4 X 14***	4 X 14***	4 X 14***
Marriage Rate	40*	40*	30**
Divorce Rate	40*	40*	30**
Married Women # of Children by Age	19****	19****	19****
Unmarried Women # of Children by Age	19****	19****	19****
Married Women Wage	40*	40*	30**
Unmarried Women Wage	40*	40*	30**
Married Men Wage	40*	40*	30**
Unmarried Men wages	40*	40*	30**
Assortative Mating	5 X 5	5 X 5	5 X 5
Wage by education level – women only	5 X 40**	5 X 40**	5 X 30**
Employment by education level – women only	5 X 40*	5 X 40*	5 X 30**
Women Health distribution	2 X 44*****	2 X 44*****	2 X 34*****
Men Health distribution	2 X 44*****	2 X 44*****	2 X 34*****

* age 21 to 61
** age 21 to 51
*** Schooling distribution from age 17 to 30, no schooling after 30.
****from age 21 to 40. No newborn after age 40.
***** Different source of data: IHIS (Integrated Health Interview Series) at the Minnesota Population Center, University Minnesota.

The initial condition is age 17, zero experience and 10 years of education. To estimate the additional parameters at stages 2 to 5 we used the same moments for the cohorts of 1935 and 1975 with a few adjustments. For the cohort of 1935 we start at age 25 and there are 1241 moments and for the cohort of 1975 we end at age 41 and there are 865 moments.

Appendix D: Parameters

Table D.1. Labor Market Parameters

Description	Parameter	Men	Women
marriage offer probability parameters			
probability of meeting a husband if below 18	omega1	0.075	
probability of meeting a husband if above 18 but in school	omega2	0.274	
probability of meeting a husband if above 18 not in school	omega3	0.450	
Probability of meeting a CG - CONSTANT	omega4	0.069	-0.269
Probability of meeting a CG if she SC	omega5	-0.985	-0.399
Probability of meeting a CG if she HS	omega6	-1.699	-1.160
Probability of meeting a SC - CONSTANT	omega7	-0.169	-0.469
Probability of meeting a SC if she HS	omega8	-0.837	-0.237
taste for marriage			
constant	psai0	1.127	
schooling gap - men more educated	psai2	-2.159	
schooling gap - women more educated	psai3	-2.754	
health gap	psai4	-0.133	
utility from pregnancy			
married	pai1	0.259	
health	pai2	-0.129	
# of kids in household	pai3	-0.854	
pregnency in t-1	pai4	-3.000	
utility from quality and quantity of children			
CES function's parameter	row0	-0.851	
wife leisure	row1	0.551	
husband leisure	row2	0.366	
spending per child	row3	0.000	
unemployment benefit		6784.300	
utility function parameters			
CRRA consumption parameter	alpha0	-0.499	
leisure when pregnant	alpha11	---	0.061
leisure by education	alpha12	0.000	0.077
leisure by health	alpha13	0.055	0.097
CRRA leisure parameter	alpha2	0.876	
utility from kids when married	alpha3_m	0.270	0.696
utility from kids when single	alpha3_s	0.036	0.527
cost of divorce parameters			
fixed cost od divorce	alpha4	-1.543	-1.662
divorce cost per chid	alpha4	-0.210	-0.323
Home Time Equation			
constant	tau0	0.001	0.001
ar coefficienr	tau1	0.715	0.973
pregnancy in previous period	tau2	0.355	1.455
utility from school			
constant	s1	0.394	0.442
mother is CG	s2	0.465	1.376
return for ability	s3	0.545	0.624
post high school tuition	s4	-1.462	

Table D.2. Labor Market Parameters

Description	Parameter	Men	Women
wage function parameters			
experience	beta1	0.056	0.054
exp^2	beta2	-0.001	-0.001
HSD	beta31	8.923	8.852
HSG	beta32	9.119	8.979
SC	beta33	9.245	9.153
CG	beta34	9.739	9.499
PC	beta35	9.913	9.683
job offer parameters - full time			
constant	lambda0_f	-0.275	-0.524
experience	lambda1_f	0.163	0.138
education	lambda2_f	0.095	0.101
health	lambda3_f	-0.422	-0.433
job offer parameters - part time			
constant	lambda0_p	0.002	-0.534
experience	lambda1_p	0.076	0.122
education	lambda2_p	0.009	0.052
health	lambda3_p	-0.427	-0.413
job offer parameters - fired			
constant	lambda0_nf	1.569	1.475
experience	lambda1_nf	0.265	0.239
education	lambda2_nf	0.099	0.105
health	lambda3_f	-0.421	-0.413

Table D.3. Variance-Covariance Matrix Parameters

Description	Parameter	Men	Women
Variance-Covariance Matrix Parameters			
ability variance	sigma(1,1)	0.566	0.599
home time shock variance	sigma(3,3)	0.282	0.261
wage error variance	sigma(5,5)	0.510	0.520
match quality variance	sigma(7,7)	0.465	
pregnancy shock variance	sigma(8,8)	0.778	

Additional parameters such as the terminal value parameters and the health distribution parameters can be found at http://www1.idc.ac.il/Faculty/Eckstein/EKL.html. The parameters of stages 2-5 can be found there as well.