What Women See in Men and Vice Versa: Estimates Based on Sex Ratios and Marriage Patterns[1]

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Abstract

Much of what looks like changing marriage preferences over the twentieth century is actually demographics. Exploiting plausibly exogenous variation in sex ratios across U.S. birth cohorts (1870, 1930, 1950), we jointly identify preferences, match quality dynamics, and the costs of marriage and divorce. Demographics alone explain two-thirds of cross-cohort differences. Women's premium for older husbands collapsed across cohorts; men's preferences barely changed. Love that survives its early years becomes permanent, but the odds of surviving fell from 97% to 44%. Divorce costs fell six-fold and depend on life stage. A horse race across behavioral channels shows that the match quality process—not mate-age preferences—is the primary dimension of generational change. Declining divorce costs and fragile match quality are substitutes: either alone fits the data, but together they reveal two independent dimensions of social change. The model validates out of sample on the 1910 and 1970 cohorts.

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JEL Classification: J10, J11, J12

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1 Introduction

Much of what looks like changing marriage preferences over the twentieth century is actually demographics. Variation in sex ratios and mortality across U.S. birth cohorts—driven by immigration and differential longevity gains—accounts for two-thirds of the cross-cohort differences in marriage and divorce behavior, with no change in behavioral parameters at all. This paper provides the first joint identification of marriage preferences, match quality dynamics, and the costs of marriage and divorce in a unified equilibrium framework, exploiting the large demographic variation across the 1870, 1930, and 1950 birth cohorts.[2]

The variation we exploit is plausibly exogenous to marriage preferences. The sex ratio at marriageable ages fell from 1.056 men per woman (1870 cohort) to 0.942 (1950 cohort)—a swing from male surplus to female surplus driven by the closing of the frontier, declining male immigration, and faster female mortality improvements. These forces operate through the population's age and sex structure, not through tastes over partners. They change who is scarce and who must compete in the marriage market, so that equilibrium marriage and divorce patterns shift even if no one's preferences change. We estimate a dynamic general equilibrium model of marriage and divorce, matching 84 moments of marriage and divorce behavior across the three cohorts. Beyond the aggregate role of demographics, the estimates reveal sharp findings about what people value and how relationships work:

- *Women's preferences changed; men's did not.* Women in the 1870 cohort placed a premium on older over younger husbands large enough to delay marriage by several years relative to a world with symmetric preferences (Figure 3). By 1950 this premium had collapsed to near zero. Men's preferences over partner age are essentially constant across all three cohorts. The marriage age gap is driven not by men preferring younger (more fecund) women, as Siow (1998) suggests, but by women's preference for older, more established men—a preference that erodes as women gain economic independence.
- *Love that survives becomes permanent—but surviving got harder.* A good match, once achieved, is permanent: the implied duration exceeds the remaining lifetime. But in the 1870 cohort a new marriage had a 97% probability of reaching the good state; by 1950, this had fallen to 44%. The 1950 cohort uniquely allowed recovery from bad matches with 16% chances, generating dynamics that resemble cohabitation.
- *Divorce costs depend on life stage.* The middle-age group ("young" in our model) faces the

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[2] Throughout we consider only opposite-sex couples, reflecting the historical period studied. For historical mortality rates, see Haines (1998) and Arias (2012); for historical patterns of gender-biased immigration to the U.S., see Donato and Gabaccia (2015).

highest effective divorce cost—roughly six times the utility value of a standard-deviation match shock—substantially above both adolescents and the old. This generates the age-declining divorce rate profile observed in every cohort. The base cost declined six-fold across cohorts, with a structural break between 1910 and 1930 coinciding with the liberalization of divorce laws and the entry of women into the labor force.

- *Divorce costs and match quality are substitutes.* Cohort-specific match quality process alone—without any cohort variation in divorce costs—achieves the same fit as the Baseline specification. Both channels govern marital dissolution, one through the price of exit, the other through the probability of wanting to exit. Combining both yields a further 14% improvement, revealing two independent dimensions of social change: the liberalization of exit and the increasing uncertainty of relationships.

How can these mechanisms be separately identified? The key is that different moments respond to different parameters, and the three cohorts provide 84 moments under very different demographic conditions. Marriage rates by age for male and female reveal how each sex values partners of different maturities: when the sex ratio shifts from male surplus to female surplus, the scarce sex becomes pickier and marriage patterns change in ways that depend on the preference parameters. Divorce rates and their age profile reveal the cost of exit: the pervasive pattern that divorce declines with age identifies the age-dependent component of divorce costs, because without it the model would predict flat or rising divorce with age. The fraction never married by age 50 disciplines marriage frictions: a high never-married fraction signals that substantial frictions prevent matches from forming. The persistence of marriages—how quickly divorce rates fall with duration—reveals match quality dynamics: if good matches are permanent but medium matches are fragile, divorce concentrates in the early years. The cross-cohort variation in these moments overdetermines the parameter vector.

The model abstracts from income, education, and fertility, allowing age to capture the key dimension along which partner characteristics vary. This is not a limitation but a design choice: it is precisely this parsimony that allows identification over an eighty-year span and the separate recovery of the age profile of divorce costs—a decomposition that richer models with more state variables cannot achieve because they lack the long demographic variation needed to pin down each channel.

The model validates both in and out of sample. The 1910 birth cohort—not used in estimation—is predicted with a fit better than any in-sample cohort, confirming that the decline in marital commitment began after World War I. The 1970 cohort cannot be matched with demographics and divorce costs alone, but full re-estimation identifies the same channels that dominate the in-sample horse race: fragile match quality and delayed maturation. This coherence between in-sample and out-of-sample findings strengthens the interpretation that the model is recovering genuine features of how human relationships changed.

This paper contributes to the literature on marriage and matching in three ways. First, it provides a framework to separate demographic forces from behavioral responses in equilibrium matching markets. Second, it identifies the dynamics of match quality and the role of divorce costs using variation that is orthogonal to preferences. Third, it shows that much of the long-run change in marriage and divorce patterns can be understood as the consequence of demographic shifts rather than changes in tastes.

Our work builds on a large literature connecting sex ratios to marriage outcomes (Becker (1981); Wilson and Neckerman (1986); Brien (1997); Seitz (2009); Choo, Seitz, and Siow (2008); Knowles and Vandenbroucke (2019)), with credible reduced-form evidence from Angrist (2002) (U.S. immigrant cohorts) and Abramitzky, Delavande, and Vasconcelos (2011) (post–World War I France). Siow (1998) pioneered the idea that biological constraints—specifically gender differences in fertility horizons—shape marriage timing; Díaz-Giménez and Giolito (2013) confirm that fecundity differences, not income, account for the age gap at first marriage. Our finding that the age gap is driven by women's preference for older men rather than men's preference for younger women offers a complementary mechanism: it is demand-side (women valuing establishment) rather than supply-side (men valuing fecundity).

A parallel literature estimates marriage market preferences using static matching models with transferable utility. Choo and Siow (2006) estimate a Becker-style matching model with multidimensional types, while Chiappori, Costa Dias, and Meghir (2017) develop semiparametric identification of matching surplus in a TU framework. Galichon and Salanié (2022) provide a comprehensive treatment of matching under TU, showing how equilibrium sorting can identify preference parameters. Dupuy and Galichon (2014) extend these methods to continuous types. Our approach differs fundamentally: we use a dynamic search model where agents meet sequentially and face frictions, rather than a frictionless assignment model. This allows us to separately identify matching frictions, match quality dynamics, and marriage/divorce costs—features that are central to the data but absent from the static TU framework. The tradeoff is that our model abstracts from income and education sorting.

Prominent explanations for the delay in marriage and the rise in divorce include declining gains from specialization (Greenwood, Guner, Kocharkov, and Santos, 2016), the contraceptive revolution (Goldin and Katz, 2002), rising income volatility (Santos and Weiss, 2016), and the closing wage gender gap (Regalia, Ríos-Rull, and Short, 2013). On the divorce side, Voena (2015) shows that the shift to unilateral divorce affected savings and labor supply, while Stevenson and Wolfers (2007) documents that no-fault laws reduced domestic violence more than they raised divorce rates—suggesting that the effective cost of divorce operates through channels beyond legal barriers. Reynoso (2024) studies the marital-sorting and welfare consequences of unilateral-divorce-law reform. These mechanisms focus on recent decades; our framework accounts for a much longer span, including the earlier cohorts that married young.

An early structural estimation of a marriage matching model is Wong (2003), who embeds the numerical solution of a two-sided matching model within a maximum likelihood procedure and finds that wage is more important than education in predicting marriageability for white men. The model we adopt here is similar in spirit to recent equilibrium marriage models used to study marriage and divorce (Aiyagari, Greenwood, and Güner (2000)), single motherhood (Regalia, Ríos-Rull, and Short (2013)), and marital sorting (Fernandez, Guner, and Knowles (2005); Choo and Siow (2006); Greenwood, Guner, Kocharkov, and Santos (2016)). Several recent papers use richer dynamic models: Goussé, Jacquemet, and Robin (2017) estimate a search model with home production and labor supply, Low, Meghir, Pistaferri, and Voena (2018) embed marriage in a life-cycle model with savings, labor market risk, and a social safety net. Shephard (2019) analyzes household formation allowing for marriage across age groups with time allocation, earnings risk, human capital accumulation, home production, and fertility. Caucutt, Guner, and Knowles (2002) study the interaction between marriage timing and fertility in a model with biological constraints. Our model is deliberately simpler—it abstracts from income, savings, fertility, and home production—because this parsimony is what makes identification possible: it allows estimation over an eighty-year span (1870–1950) and the separate recovery of the age profile of divorce costs, a decomposition that richer models cannot achieve without the long demographic variation our approach requires. Our work is also related, albeit less so, to the literature that examines the economic implications of demographic change (De Nardi, Imrohoroğlu, and Sargent (1999), Ríos-Rull (2001), Attanasio and Violante (2005)).

The rest of the paper proceeds as follows. Section 2 describes the data and the demographic variation across cohorts. Section 3 presents the model. Section 4 discusses estimation and identification. Section 5 builds up to the Baseline. Section 6 conducts the horse race across behavioral channels and performs counterfactual decompositions. Section 7 provides out-of-sample validation. Section 8 concludes. An online appendix contains full parameter tables for all nine specifications, detailed model fit tables, sensitivity to the weighting matrix, results without age-dependent divorce costs, computational details, equilibrium properties, and additional fit diagnostics for age at first marriage and never-married fractions.

2 Data Properties and the Logic of the Estimation

Over the last hundred plus years there have been large differences in the age and sex structure of the U.S. population, mostly due to a huge increase of life expectancy, especially for women who, in addition to increased survival at older ages, have also experienced a dramatic reduction in the mortality associated with childbearing. Immigration has also played a part as it has varied over time while being more male intensive in the earlier period. As a result of these changes, there has been a large switch in the sex ratio of adults (which we take to be those between 20–44). It went from 1.056 males to females for the cohort born in the decade starting in 1870, to 0.952 for the cohort born in the 1930s, to 0.942 for the cohort born in the 1950s (top panel of Table 1).

Some marriage patterns have been consistent over this period (e.g. that most people marry, that men marry older, that divorce is much rarer than marriage). Yet, some other marriage patterns have experienced large changes (bottom panel of Table 1). Among those that affected both sexes similarly were the noticeable increase in the fraction of people married,[3] the enormous increase in divorce (the divorce rate went from less than 1‰ to over 5‰), and, most interestingly for our purposes, there was an asymmetric change in the age at first marriage that decreased by 1.2 years for women and by 2.7 years for men.

Table 1. Trends in Demographics and Marital Statistics, 1870-1950

	Birth Cohort			% Change
	1870	1930	1950	in the Data
Demographics				
Sex ratio (age 20–44)	1.056	0.952	0.942	-10.9
Life expectancy at age 15 (female)	49.7	63.8	65.2	31.1
Life expectancy at age 15 (male)	49.0	56.5	59.9	22.1
Some Marriage Properties				
Age at first marriage				
Females	22.1	19.9	20.9	-5.4
Men	25.9	23.1	23.2	-10.4
Married as % of those aged 16 to 49				
Females	59.7	72.6	62.5	4.7
Men	48.4	63.9	56.6	17.0
Divorce rate, per 1,000 people	0.7	2.2	5.2	642.9

Note: Numbers are calculated from IPUMS Census microdata (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010). See Online Appendix A for details.

We exploit the link between sex ratios and age of marriage that this table suggests. In particular, we take advantage of finer information about age specific patterns and hence we use age-specific marriage

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[3] The increase in the relative number of women to men makes the increase of incidence asymmetric: the fraction married increased modestly for women (59.7% to 62.5%) while it increased dramatically for men (48.4% to 56.6%).

and divorce rates experienced by a subset of the cohorts born since 1870.[4] Table 2 displays those rates in addition to the incidence of marriage (the fraction to ever marry or its complement, those that never married) and the age at first marriage. There are some properties common to all cohorts. Marriage rates rise then fall with age, peaking between the ages of 20 to 24 both for males and females. Despite the fact that marriage rates for males and females peak during the same age range, males' rates are low relative to those of females before the age of 25, and high relative to females' rates after the age of 25. These patterns are consistent with the well documented fact that males tend to marry younger females. For both males and females, the divorce rates are highest at the youngest ages and decrease (almost) monotonically after that. The data on the never-married implies that males have both higher rates of entry-into and exit-from marriage (especially given the low sex ratio of the 1950 birth cohort). Finally, age at marriage is lower for females than males.

Table 2. Marital Statistics Target: 1870, 1930 and 1950 Birth Cohorts

	1870 Birth Cohort		1930 Birth Cohort		1950 Birth Cohort	
	Female	Male	Female	Male	Female	Male
Marriage Rate						
16-19	97.9	20.5	151.2	48.2	123.2	58.7
20-24	126.7	102.3	216.9	181.2	170.3	148.8
25-29	82.4	86.5	115.0	137.2	95.7	111.7
30-34	65.6	70.2	44.5	80.1	46.4	55.8
35-39	28.4	42.7	21.2	31.9	32.2	39.2
40-44	24.6	48.8	21.6	42.2	16.0	24.6
Divorce Rate						
16-19	2.5	2.5	12.9	11.6	16.4	18.3
20-24	1.9	1.8	8.9	9.2	25.4	23.0
25-29	1.3	0.6	4.7	4.4	23.9	23.3
30-34	1.5	1.1	5.5	4.2	10.8	10.1
35-39	0.4	0.7	3.8	3.1	15.7	13.3
40-44	0.3	1.2	8.1	7.2	6.8	6.6
Never-Married by Age 50	11.4	13.0	4.6	6.0	7.7	9.4
Age at First Marriage	22.1	25.9	19.9	23.1	20.9	23.2

Note: Marriage rates are measured per 1,000 single individuals while divorce rates are per 1,000 married individuals. Calculated from IPUMS Census microdata (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010). See Online Appendix A for details.

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[4] We choose cohorts as far away as possible because we want to avoid overlap of individuals across our analysis. We added the 1930 cohort because of the large variation in marriage behavior that it experienced.

There are other notable differences across cohorts that are not monotonic in the sex ratio. As shown in Tables 1 and 2, between the 1870 and 1950 cohorts there is

- a roughly 30% reduction in the never-married fraction at age 50—from 11.4% to 7.7% for women and from 13.0% to 9.4% for men (Table 2);
- an enormous, more-than-sevenfold increase in the aggregate divorce rate, from 0.7 to 5.2 per 1,000 (Table 1);
- as a consequence, a noticeable increase in the fraction married, especially for men (48.4% to 56.6%, Table 1);
- a reallocation of women's marriage hazards across age—less marriage in the early thirties (30–34: 65.6 to 46.4) and a bit more in the late thirties (35–39: 28.4 to 32.2)—while men marry less throughout the thirties and forties (Table 2);
- a fall in the age at first marriage of roughly 2.7 years for men (25.9 to 23.2) and 1.2 years for women (22.1 to 20.9, Table 1).

While these differences between the 1870 and 1950 cohorts are substantial, they are dwarfed by the contrast of either cohort with the 1930 cohort:

- the never-married fraction in 1930 was less than two thirds of the 1950 level (4.6% vs 7.7% for women, 6.0% vs 9.4% for men, Table 2);
- the age at first marriage was the lowest of the three cohorts—about two years below 1870 for both sexes, and about a year below 1950 for women (with men's 1930 and 1950 ages essentially tied, Tables 1 and 2);
- marriage was concentrated much more heavily at the youngest ages: female marriage rates at 16–19 (151.2) and 20–24 (216.9) exceed both neighboring cohorts by a wide margin (Table 2);
- only the divorce rate falls in between the other two cohorts (2.2 in 1930 vs 0.7 in 1870 and 5.2 in 1950, Table 1).

Given these changes in behavior and associated changes in fundamental demographics, we follow the strategy of posing and estimating a dynamic equilibrium model of marriage and divorce. We take the model to confront the data from each of the three cohorts as different steady states of environments with different sex ratios and age compositions. To assess the contribution of the different demographics, we start by posing common demographics and report how the model would try to account for the three sets of data, obviously an impossible task. We then confront the model with each of the cohorts noting how each cohort has different demographics but identical preferences. We then look at how the fit may improve by allowing some properties of preferences to change.

3 The Model

3.1 Model Ingredients

We pose a very simple multiple-age model where there is a role to marry and divorce. We abstract from additional attributes of agents (education, income, wealth, parental status). This is a deliberate choice: age subsumes much of the variation in these attributes that matters for marriage. Earnings profiles, fertility, and physical attractiveness are all strongly age-dependent, and our maturity types capture these margins in reduced form. Adding income or education as separate state variables would substantially increase the state space and the number of parameters without providing clear identification gains—the demographic variation we exploit (sex ratios and mortality) operates primarily through the age channel. Moreover, our 100-year estimation window predates the large-scale changes in female educational attainment and labor force participation that would make education a first-order marriage market attribute; for the 1870 and 1930 cohorts, age was the dominant observable characteristic in marriage markets. To model age as perceived by the other gender, we pose a model with 3 ages and exponential aging where the estimated aging parameters imply a change of how much a partner is liked. Further, we assume that mortality is age-independent which makes the stationary population of the environment consist of only three age-groups. Consequently, current age only matters through the eyes of possible partners and we typically refer to it as maturity. Finally, the analysis is under the conditions of a stationary population which is what allows us to estimate the model (the demographic details including the sex ratio variation are in Section 3.2).

Every period agents may die, but if they survive, they choose whether to marry or not, if single and matched, and whether to divorce or not, if married (details in Section 3.3). It takes both agents to agree for marriage to occur, but it only takes one to want to divorce. Both marriage and divorce carry costs when they happen and there are frictions in matching as every period (a year) there is at most a match with one other person, with the odds depending on the relative supplies of unmarried males and females (outlined in Section 3.5 after taking care of record keeping the agents' types in Section 3.4). Combined with the differential life expectancies of males and females, the relative abundance of agents of each sex allows us to capture gender differences in the incentives to delay marriage and to divorce. Being married yields utility (or disutility) that depends on the maturity of the spouse and on a Markovian idiosyncratic *quality of the match* shock. In addition, both being single or married has an individual associated temporary shock of the extreme value variety. Preferences and individuals' decisions are in Sections 3.6 and 3.7, respectively. Section 3.8 defines the steady-state equilibrium.

3.2 Demographics

Agents differ in sex (male and female), $g \in \{m, f\}$, and maturity (adolescent, young, and old), $i \in \{a, y, o\}$, beginning their lives as adolescents. While sex is a permanent fixture of agents, an individual's maturity switches forward stochastically with transition probabilities $\Gamma^{g}_{i,i'}$, and, importantly, differently for males and females. Obviously, agents also differ in how long they have been alive, their age (a backward notion), which is relevant for record keeping, but not for the determination of behavior. Agents of any maturity can make contacts and form matches. Maturity (adolescent, young, or old) is not observed in the data, where only age in years is recorded, but it is observed by the agents in a match, partially determining how attractive each one of them is. Death happens with constant, gender-specific probability π^{g}.

The measure of females is normalized to 1, and we denote the total number of males by x^{m}. To keep the population stationary, each period there is an inflow of single adolescent females n^{f}, that equals the outflow of females through death. We pose a constant measure of new adolescent males that may differ to that of females which we attribute to net migration[5] and that allows for the sex ratio to differ from the one implied by differences in life expectancy. The measure of new adolescent single females that keeps the population constant is

$$n^{f} = \pi^{f}. \tag{1}$$

3.3 Match Quality

At the beginning of each period an agent can be in one of three marital states: single unmatched ($z = 0$), single matched, ($z = 1$), and married ($z = 2$). All couples date before becoming married. Singles include those never married, divorced, and widows. Matched and married agents draw their own assessment of the match quality, q, that has two components, a Markov component and an i.i.d. component, $q = \mu + \epsilon$. These two variables are different for each member of the couple. The Markov component, $\mu \in \{\mu_L, \mu_M, \mu_H\}$, is initially drawn from $\Lambda_0(\mu)$ and has transition $\Lambda_{\mu,\mu'}$ (throughout the paper, primes denote next period values, while asterisks, *, denote the associated variable of the "other" —the agent matched with— as is customary in international economics). The transitory component,

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[5] While a few more males than females are born (with small variations across space and time), the higher mortality of males implies that by the time adolescence arrives the numbers are very similar.

ϵ, follows a type 1 extreme value distribution with mean zero and scale parameter 1. While the variance of ϵ is fixed, it is not a constraint, but a normalization, given the unrestricted nature of the values of μ.

3.4 States and Aggregates

An agent is characterized by its sex and maturity, $\{g, i\}$ as well as by whether it is single unmatched, single matched, or married, z, and if so, what is the maturity of the partner, i^* and the quality of the match as assessed by itself q, and its partner q^*. It is more convenient to keep track of the state before realization of the extreme value shocks ϵ. We separate the state into purely exogenous variables (sex and maturity) that we write as super-indices and those that partly depend on choices that we denote s, so when matched or married we have $s = \{z, i^*, \mu, \mu^*\}$ for an agent and $s^*(s) = \{z, i, \mu^*, \mu\}$ for its partner while when unmatched we write $s = 0$. We have then that $x^{g,i}(z, i^*, \mu, \mu^*)$ is the measure of agents of sex g and maturity i that are matched in a type z relationship with a partner of maturity i^*, and assessments of the quality of the match μ and μ^*. Since every matched male must be with a matched female, we have that

$$x^{f,i}(z, i^*, \mu, \mu^*) = x^{m,i^*}(z, i, \mu^*, \mu), \qquad \forall\, z \in \{1, 2\}, i, i^*, \mu, \mu^*. \tag{2}$$

Aggregation over ages yields $x^g(z, i^*, \mu, \mu^*) = x^{g,a}(z, i^*, \mu, \mu^*) + x^{g,y}(z, i^*, \mu, \mu^*) + x^{g,o}(z, i^*, \mu, \mu^*)$ and $x^g(0) = x^{g,a}(0) + x^{g,y}(0) + x^{g,o}(0)$.

3.5 Matching Technology

Matching depends on the sex ratio of available agents, the ratio of potential spouses to potential competitors. In particular, those of the sex in short supply meet a potential spouse with certainty, while those of the opposite sex are rationed. Consequently, single agents, (the newborn, and those surviving and either previously unmatched, or previously matched who did not marry, or previously married and divorced), meet a partner with probabilities given by

$$\psi^f = \min\left\{1, \frac{x^m(0) + x^m(1, .)}{x^f(0) + x^f(1, .)}\right\}, \tag{3}$$

$$\psi^m = \min\left\{1, \frac{x^f(0) + x^f(1, .)}{x^m(0) + x^m(1, .)}\right\}. \tag{4}$$

The measures of singles $\{x^f(0), x^m(0)\}$ and matched $\{x^f(z, i^*, \mu, \mu^*), x^m(z, i^*, \mu, \mu^*)\}$ refer to the situation after the matches have occurred which we take to be at the beginning of the period. Note that for simplicity we assume that there is no bias towards matching within the same maturity.

3.6 Preferences

Preferences differ by gender and marital status. Single agents get zero utility (a normalization). Married agents that did not change marital status get utility based on their own gender's assessment of the maturity of the spouse and on their own assessment of the match quality, $\alpha^g_{i^*} + \mu$. Change of marital status is costly (or rewarding). An agent that gets married this period gets disutility $\phi > 0$, while one that gets divorced gets disutility $\omega > 0$. We write $u^{g,i}(s, z') = \alpha^g_{i^*} + \mu - \phi$ when $z = 1$, $z' = 2$ (the agent is getting married), and $u^{g,i}(s, z') = \alpha^g_{i^*} + \mu$ when $z = 2$ and $z' = 2$ (the agent remains married). Agents discount the future at rate β. In addition agents are hit by a pair of Gumbel shocks $\{\epsilon^1, \epsilon^2\}$, with mean zero and scale parameter 1 that add to the value of being single or married.

3.7 Value Functions

The value for a single unmatched agent of gender g and maturity i is

$$\begin{aligned}\Omega^{g,i}(0,0) \; &= \beta \;(1-\pi^g)\; \sum_{i'} \Gamma^g_{i,i'} \Bigg\{ \;(1-\psi^g)\; V^{g,i'}(0) \\ &\qquad + \psi^g \sum_{i^*,\mu,\mu^*} \frac{x^{g^*,i^*}(1,.)}{x^{g^*}(1,.)}\; \Lambda_0(\mu)\; \Lambda_0(\mu^*)\; V^{g,i'}(1, i^*, \mu, \mu^*) \Bigg\}. \qquad (5)\end{aligned}$$

The expected value of entering the next period unmarried, involves the consideration of whether the subsequent period will be matched or unmatched. In the last term, $\frac{x^{g^*,i^*}(1,.)}{x^{g^*}(1,.)}$ is the probability of drawing a maturity i^* partner conditional on matching which follows from our assumption of non-own-maturity bias in matching. Note also that because of the zero expected value of the extreme value shocks the expected value of being single is also $V^{g,i}(0)$.

The values for matched agents depend on the actions of both members of the couple. Not only the agent has to know what it likes, but also the circumstances under which the agent with whom it is matched will be willing to become or remain married. The value that the agent gets conditional on being or becoming married is in addition to the extreme value shock

$$\begin{aligned}\Omega^{g,i}(s,2) = u^{g,i}(s,2) \;+\; \beta\,(1-\pi^g) \Bigg[(1-\pi^{g^*}) \sum_{i',i^{*\prime},\mu',\mu^{*\prime}} \Gamma^g_{i,i'} \Gamma^{g^*}_{i^*,i^{*\prime}} \Lambda_{\mu,\mu'} \Lambda_{\mu^*,\mu^{*\prime}}\; V^{g,i'}(2, i^{*\prime}, \mu', \mu^{*\prime}) \\ + \pi^{g^*} \sum_{i'} \Gamma^g_{i,i'} \Big((1-\psi^g) V^{g,i'}(0) + \psi^g \sum_{i^{*\prime},\mu,\mu^*} \frac{x^{g^*,i^{*\prime}}(1,.)}{x^{g^*}(1,.)}\; \Lambda_0(\mu)\Lambda_0(\mu^*) V^{g,i'}(1, i^{*\prime}, \mu, \mu^*)\Big)\Bigg]. \qquad (6)\end{aligned}$$

Some discussion is needed. The first line of this expression includes the current utility and the part of the continuation value that involves remaining married. It requires survival, and it takes the expectation over future ages and assessments of the quality of the marriages of both partners including their persistence. The second line involves the utility that ensues if becoming a widow with its subsequent possibilities of being matched or not.

If a matched agent gets divorced, its value in addition to the extreme value shock associated with being single is

$$\Omega^{g,i}(s,0) = \Omega^{g,i}(0,0) - \omega. \tag{7}$$

This is, it gets the cost of divorcing today and the value of being single. The agent would like to choose the solution to

$$\max \ \left\{ \Omega^{g,i}(s,2) + \epsilon^2, \ \Omega^{g,i}(s,0) + \epsilon^1 \right\}. \tag{8}$$

A matched agent has a say on its marital status only if the other agent in the match is willing to be married, otherwise it will become single. The properties of extreme value shocks imply that the probability that an $\{i, g, s\}$ agent prefers to be married is

$$p^{g,i}(s) = \frac{\exp\left[\Omega^{g,i}(s,2)\right]}{\exp\left[\Omega^{g,i}(s,0)\right] + \exp\left[\Omega^{g,i}(s,2)\right]} \tag{9}$$

We can now obtain the beginning of period value for matched or married (given the decision rule of the partner if any) $s = \{z, i^*, \mu, \mu^*\}$ using again the convenient extreme value formula (see Online Appendix B for the derivation)

$$V^{g,i}(s) = \ln\left[\exp \Omega^{g,i}(s,2) + \exp \Omega^{g,i}(s,0)\right] p^{g^*,i^*}(s^*(s)) + \Omega^{g,i}(s,0)\left[1 - p^{g^*,i^*}(s^*(s))\right], \tag{10}$$

where obviously $p^{i,g}(0) = 0$.

3.8 Steady State Equilibrium

A steady state is just a set of measures $x^{g,i}(s)$, values $V^{g,i}(s)$, and choices $p^{g,i}(s)$ such that agents choose optimally, and their choices both generate the value functions and yield the measures as steady state distributions of agents. It is standard, so no need of further formality.[6]

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[6] We do not have a proof of uniqueness for this class of models (see Burdett and Coles, 1997, for a discussion of multiplicity in two-sided search). In practice, our numerical algorithm converges to the same equilibrium from a wide range of initial conditions, and we keep focusing on the same equilibrium across the cohorts in the estimation.

4 Estimation

We estimate the model using the method of moments. We take each cohort (sufficiently separated from each other) to be in a stationary equilibrium with the life expectancy and sex ratios described in Table 1. We assume that each cohort lives under a different demographic regime that shapes the relative availability by age of men and women. These regimes are determined by a combination of mortality and fertility/immigration that differs by age. Demographics properties (mortalities and sex ratios) are the only features that are directly observable and vary across cohorts and, consequently, they play a central role in our analysis. We then estimate different versions of the model varying which elements are commons across cohorts using data for all cohorts.

In our setup, a model period corresponds to one year. We assume both men and women enter the economy at age 16, and we track their calendar age in order to calculate the marital status targets.[7] Mortality determines the exit of agents in the model and it plays three roles in the analysis. *(i)* A fall in mortality rates for the opposite sex implies an increase in the expected future value of marriage, as the probability of remaining married in the future increases. *(ii)* Mortality affects the marriage opportunities for males versus females through the sex ratio. That is, if mortality rates fall to a greater extent for females than for males, as we observe in the data, then males are predicted to experience an improvement in marriage market conditions. Thus, we expect the fall in mortality to benefit males more than females along two dimensions: the value of marriage increases because one's current spouse is more likely to survive and the value of being single increases as one's marriage market improves. *(iii)* The age composition of the population is determined by mortality rates, where a fall in mortality rates is consistent with an increase in the average age in the population.

Fertility/immigration determines the entry of agents in the model. As we are only interested in adults, it is not necessary to distinguish between the two forms of arrival of new agents. We normalize the stock of females and males at age 16 to one each, and calibrate a migration term i^m added to the male stock at age 20 so that the sex ratio of the population aged 20–44 in the model matches the data for each cohort.[8] An increase in the immigration rate serves two roles in the model, similar to the effect of a fall in the male mortality rate. *(i)* Marriage market conditions for females improve as immigration for males increases, as more potential husbands become available. *(ii)* An increase in the immigration rate results in a decrease in the average age of men in the model.

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[7] Remember that agents' maturity ($i \in \{a, y, o\}$) changes stochastically over their life-cycle. Therefore, individuals at the same calendar age could differ in their maturity. The distributions of the adolescent, the prime, and the old at certain age are determined by the transition probabilities, $\{\Gamma^f_{a,y}, \Gamma^f_{y,o}, \Gamma^m_{a,y}, \Gamma^m_{y,o}\}$. We estimate the transition probability parameters so that the model can fit the marriage and divorce rates by age group.

[8] In the U.S. IPUMS Census data, sex ratio imbalances first appear around age 20 of the cohorts, reflecting immigration at those ages in the cohorts.

We select in Section 4.1 the functional forms and we list the parameters that we need to estimate. Section 4.2 discusses the set of moments that we use in the estimation. The technical details of the estimation are in Section 4.4.

4.1 Parameters

For a given cohort there are 22 parameters in addition to the discount factor which we set equal to 0.96 annually. We divide those parameters into seven groups: A) demographic parameters, B) divorce cost parameter, C) preference parameters, D) the parameters for the aging process, E) the parameters for the match quality process, F) marriage cost parameter, and G) age-dependent divorce cost parameters. All specifications include the G parameters. The A parameters that determine the initial sex ratio and the mortality rates are determined outside the model as they are assumed to not depend on marriage patterns. Each set of parameters is discussed in turn below.

A. Demographics (3 parameters) There are 2 mortality parameters that determine life expectancy of each sex, $\left\{\pi^f, \pi^m\right\}$. There is also the number of new male adolescents in each cohort which together with the differential mortality determines the sex ratio for the cohort: $\left\{i^m\right\}$.

B. Cost of Divorce (1 parameter) We assume that the cost of divorce is symmetric for males and females which adds one parameter ω.

C. Preferences (6 parameters) The current period utility function takes the form: $u^g(j) = \alpha_j^g + q$ for married males and females and $u^g(0) = 0$ for singles. Preferences for a matched agent depend on gender and on the age of the agent's spouse and match quality. Therefore, there are 6 preference parameters to be determined: $\left\{\alpha_a^f, \alpha_y^f, \alpha_o^f, \alpha_a^m, \alpha_y^m, \alpha_o^m\right\}$.

D. Aging Process (4 parameters) Recall that we assume all males and females start out adolescent and age stochastically over time and that they may age at different speeds. As a result, there are 4 parameters governing the aging process $\left\{\Gamma_{a,y}^f, \Gamma_{y,o}^f, \Gamma_{a,y}^m, \Gamma_{y,o}^m\right\}$.

E. Match Quality Process (5 parameters) Agents decide whether they get married or not after observing the realization of match quality. As stated, match quality consists of two parts, a Markov chain and an i.i.d. component. We pose a three state Markov chain with an initial distribution where everybody starts in the middle state when a couple meets for the first time (thus, $\Lambda_0(\mu_M) = 1$, and $\Lambda_0(\mu_L) = \Lambda_0(\mu_H) = 0$). If a couple decides to continue marriage, the Markov component of their match quality evolves according to a common transition matrix even though future realizations across sexes may vary:

$$\begin{pmatrix} \Lambda_{HH} & 1-\Lambda_{HH} & 0 \\ \Lambda_{MH} & 1-\Lambda_{MH}-\Lambda_{ML} & \Lambda_{ML} \\ 0 & 1-\Lambda_{LL} & \Lambda_{LL} \end{pmatrix}.$$

We also assume that the gain from marriage of the Markov component is symmetric with mean zero; $\mu_H = -\mu_L = \theta$ with $\theta \geq 0$, and $\mu_M = 0$. The temporary shocks are also specific to each member of the couple and are type 1 extreme value with zero mean and scale parameter equal to 1. Notice that the values for age specific attractiveness and the Markovian match quality makes this choice a normalization rather than a restriction on parameter values. Thus, there are 5 parameters involved in the match quality process $\{\theta, \Lambda_{HH}, \Lambda_{MH}, \Lambda_{ML}, \Lambda_{LL}\}$.

F. Cost of Marriage (1 parameter) We assume the cost of marriage is the same for both sexes. Therefore, there is 1 parameter which governs the cost of marriage, ϕ.

G. Age-Dependent Divorce Cost (2 parameters) The cost of divorce depends on the agent's maturity. The effective divorce cost is $\omega(i) = \omega + \delta(i)$ where $\delta_a = 0$ (normalization), and δ_y and δ_o are estimated. This adds 2 parameters that are common across cohorts: $\{\delta_y, \delta_o\}$.

4.2 Targets

We have 93 targets or moments overall (31 per cohort). Of those, 9 targets (3 per cohort), (those in the top panel of Table 1), describe the sex and age composition of the population and are used to determine the demographic parameters of the economy without solving the model (A parameters).

The other 84 targets (28 per cohort) summarize detailed marriage and divorce behavior by age and sex as well as the incidence of marriage and the average age of first marriage are shown in Table 2. They are used to estimate the rest of the parameters. We pose various specifications of the model that differ in what are the features, as described by sets of parameters, that are shared by the various cohorts.

Demographics (3) We want to highlight the different sex ratio across cohorts of people 20–44, and because of changes in life expectancy, we also target the different life expectancy at age 15 that men and women had in each cohort. The details of the data sources and how we obtain these statistics are in Online Appendix A. The values of the demographic targets are in the first three lines of Table 1.

Marital Statistics (28) We summarize the marriage and divorce patterns for each cohort with 28 statistics. First, we use the marriage rates at different ages. Therefore, we target the marriage rates for the relevant unmarried population for six age groups for each sex for each birth cohort (12 targets). Next, we target the divorce rates of the married couples for six age groups (12 targets). The third set of targets involve the incidence of marriage. We target the fraction of males and females who never marry by the age of 50 (2 targets). Finally, we also target the age at first marriage for each sex (2 targets). Again, Online Appendix A describes the data sources and the details of how we obtained the target values. The actual values for the marital statistics targets are in Table 2.

4.3 Identification

As discussed in the introduction, different observable moments respond to different parameters. Table 3 formalizes the mapping.

Ex post evidence. The estimation results presented in Sections 5 to 7 provide ex post confirmation that identification operates as described above: demographics discipline preferences (the D specification produces implausible values that resolve once ω is freed); entry and exit costs are sharply separable ($D+\phi$ fits 37% worse than $D+\omega$ at the same parameter count); match quality and divorce costs tap independent variation (each alone achieves the same fit, but combining them yields a further 14% gain); and the channel ranking is robust across three measurement approaches and confirmed out of sample. Online Appendix C reports standard errors and a formal assessment of parameter precision.

Limitations. As with any structural estimation, identification is joint: all parameters are simultaneously determined by the full set of moments. We do not have an instrument that isolates a single parameter in a reduced-form sense. The arguments above describe the primary sources of variation that pin down each group of parameters, but they operate within the structure of the model.

4.4 Estimation

It is important to note that it is impossible to match all the moments with our model, even if it perfectly described the preferences of agents. The reason is that simply, the U.S. population is not in a stationary state and the realized marriage rates by age cannot be consistent with the marriage stocks of the stationary population. We think that proceeding with the estimation of the model under the assumption that the U.S. data is generated by the model is not very productive. This said, we want to find the parameters that do the best job in accounting for the realized marriage rates of each cohort. Consequently, we proceed by obtaining parameters via a minimum distance estimator and using the sum of the squares of the deviations of model generated data and U.S. data as a measure of goodness

Table 3. Mapping from Moments to Parameters

Parameter	Key Moments	Identification Logic
Preferences over maturity (α)	Age-specific marriage rates; partner age distributions; age gap in marriages; cross-cohort variation in these moments	Changes in sex ratios shift the relative availability of partners at different ages. The resulting changes in sorting patterns and marriage rates across ages reveal the relative valuation of partners by maturity and across sexes.
Match quality dynamics (Λ)	Age profile of divorce rates; duration of marriages; cohort differences in divorce timing	Persistence of match quality determines continuation values within marriage. Higher persistence implies longer marriages and lower early divorce, while more transitory quality leads to higher turnover. Variation in divorce timing across cohorts identifies these dynamics.
Divorce costs (ω)	Level of divorce rates; decline of divorce with age; cross-cohort differences in divorce incidence	Divorce costs affect the willingness to exit a given match. They are identified from the level and age gradient of divorce rates, as well as variation across cohorts that cannot be explained by demographics or match quality alone.
Marriage frictions (ϕ)	Marriage rates relative to implied meeting probabilities; differences between contact and marriage formation	Given that meeting probabilities are pinned down by sex ratios, deviations between predicted and observed marriage rates identify frictions that prevent matches from forming into marriages.

of fit.

The actual estimation consists of two steps. In the first step, we determine the values of the demographic parameters (the A parameters) that generate the observed sex ratios and life expectancies. This does not require solving the model, in fact it is just a simple system of 3 equations and 3 unknowns (except for an introductory estimation that poses a common demographic structure for all cohorts) implying that in this step parameters are exactly identified. For the introductory estimation that poses a common demographic structure for all cohorts, we target the average of sex ratios and life expectancies across the three cohorts.

In the second step, we estimate the remaining parameters by the Minimum Distance Estimation Method targeting the moments described above. The idea is as follows: given an arbitrary set of parameter values and the predetermined demographic parameters, we solve the equilibriumfor the demographic structure associated with each cohort. Once the equilibria are solved, we calculate the model's counterparts of the marital statistics targets and compute the square of the differences between the moments in the data and in the model. The function that we minimize is a weighted sum of these squared differences, which typically involve thousands of computations of equilibria given the large number of parameter values that we have. We choose the weighting matrix, $\mathbf{W}$, as a diagonal matrix with weights that reflect the scale of each moment group. We set the weight for marriage rates to 1, divorce rates to 100, age at first marriage to 10^{-3}, and the fraction never married by age 50 to 0.1. Divorce rates are upweighted because they are an order of magnitude smaller than marriage rates; without the 100× factor, the estimator would effectively ignore them. The age and never-married weights are downweighted to prevent these four moments (out of 84) from dominating the objective. This scheme follows Altonji and Segal (1996) in scaling weights to offset differences in magnitudes. In Online Appendix F we show that the estimates are robust to an alternative scheme that equalizes marriage and divorce rate weights and drops the age and never-married targets entirely.

5 Arriving at the Baseline

We build up explanatory power in three steps: common demographics (Pooled), cohort-specific demographics (D), and cohort-specific divorce costs ($D+\omega$, our Baseline).

Table 4. Estimated Parameters with Age-Dependent Divorce Costs, 1870–1930–1950

	Pooled (19)	D (19)	$D{+}\omega$ (Baseline) (21)		
Cohort variation in:	none	demographics	demographics + divorce cost ω		
Cohort	All	All	1870	1930	1950
(C) Preferences					
α_a^f Female pref. adol. male	−840.27	−56.43	−43.67 (25.35)		
α_a^m Male pref. adol. female	−438.09	−5.42	−5.77 (5.27)		
α_y^f Female pref. young male	24.15	−41.97	−2.01 (1.62)		
α_y^m Male pref. young female	0.96	0.20	1.35 (0.05)		
α_o^f Female pref. old male	594.81	362.96	26.80 (5.88)		
α_o^m Male pref. old female	−0.75	−1.41	−0.54 (0.04)		
(D) Aging (implied ages: young / old)					
Female	17.5 / 29.6	17.4 / 30.3	18.4 / 26.7		
Male	18.9 / 31.2	18.6 / 31.6	19.1 / 26.6		
(D) Aging transitions $\Gamma_{a,y}$, $\Gamma_{y,o}$ †					
Female	.67, .05	.71, .04	.41, .12		
Male	.35, .04	.38, .03	.32, .13		
(F) Marriage cost					
ϕ	19.69	18.23	10.34 (0.04)		
(E) Match quality †					
θ (gain in H-state)	1.00	0.30	0.50 (0.02)		
Λ_{HH} ‡	1.000	1.000	1.000 (—)		
Λ_{MH}	.17	.31	.17 (.012)		
Λ_{ML}	.83	.69	.83 (.012)		
Λ_{LL}	.92	.97	.99 (.006)		
(B) Divorce cost					
ω	8.23	7.19	13.18 (0.59)	5.30 (0.61)	2.17 (0.25)
(G) Age-dependent divorce-cost offsets					
δ_y (young)	2.71	3.19	2.50 (0.14)		
δ_o (old)	0.25	1.34	0.31 (0.04)		
WSSE	0.201	0.067	0.056		
AWSSE	0.260	0.087	0.074		
reduction vs. Pooled	—	67%	72%		

Notes for Table 4. The three columns correspond to nested specifications that progressively allow more dimensions of cross-cohort variation. **Pooled** treats the three cohorts as one: a single set of 19 behavioural parameters and common demographic inputs. D keeps the same 19 behavioural parameters but lets the demographic environment (sex ratios, mortality, age composition) differ by cohort. $D{+}\omega$ **(Baseline)** adds two more parameters: the divorce cost ω is now estimated separately for each cohort, while the remaining 19 parameters are still common.

Standard errors for the Baseline specification are reported in parentheses next to each estimate (84-target sandwich VCE with finite-difference Jacobian; see Online Appendix C); for cohort-invariant parameters the Baseline value applies to all three cohorts. SEs for the Pooled and D columns are not reported (the sandwich computation was run only for the Baseline). The Γ and Λ rows marked † are smooth (logistic / multinomial-logit) transforms of raw parameters, with delta-method SEs. Baseline Γ SEs are (.015, .006) for the female row and (.016, .013) for the male row (reported here rather than inline to keep the row visually consistent with the rest of the column). $\Lambda_{HH}{}^{\ddagger}$ sits at the lower-bound corner of the parameter space, so its raw-parameter Jacobian column is numerically zero under $\epsilon = 0.01$ and the SE is reported as "—". WSSE is the weighted sum of squared errors at the optimum across 84 marital-statistics targets; AWSSE is the analogous quantity for the 9 demographic targets; "reduction vs. Pooled" gives the relative WSSE improvement.

5.1 Common Preferences and Common Demographics (Pooled)

This specification assumes a common demographic process that poses the average sex ratio found for all three cohorts as well as the average life expectancies across the three cohorts. All preference parameters are common, and the divorce cost is a single common level augmented by age-dependent offsets (δ_y, δ_o). Beyond the three demographic parameters, we estimate 19 parameters against the 84 target moments. Here, we are not using demographic variation for our estimates, so we should interpret these estimates as the best job that the model could do to minimize the distance between the model moments and the average of the corresponding moments across the three cohorts.

In the last rows of Table 4 we show our measures of fit. The first is the weighted sum of squared errors (WSSE). The measure by itself does not tell us much, but it is very useful when we differentiate the demographics in the model. The second row reports the adjusted WSSE, which penalizes over-parameterization:

$$\text{AWSSE} = \text{WSSE} \times \frac{N}{N-k}, \tag{11}$$

where $N = 84$ is the number of target moments and k is the number of estimated parameters. This correction inflates the objective function for specifications that achieve better fit by adding parameters rather than through genuinely better identification. The third row reports the percentage reduction in WSSE relative to this specification, which does not include any parametric variation in the fundamental demographics (hence the zero value for this version of the model).

The WSSE for this specification is 0.201. Even without demographic variation, the age-dependent divorce cost allows the model to generate a declining divorce rate profile across age groups, which is a pervasive feature of the data.

5.2 Different Demographics (D)

The third column of Table 4 displays the estimates of a model where all preference parameters are constant across cohorts, demographics differ, and the divorce cost has age-dependent offsets but a common level. This is the simplest specification that carries out the central idea of this paper: using demographic variation to identify preference parameters. Under this specification, agents see different odds of meeting over time and are also aware that so do their prospective partners, which induces different behavior in them. The WSSE falls dramatically from 0.201 to 0.067—a 67% improvement—indicating that demographics is the dominant source of the cohort variation.

However, the estimated parameters for this specification reveal identification problems: the preference for old males reaches 363 and the implied transition age into the old state exceeds 40 for both sexes, values that are economically implausible. The model compensates for the inability to fit cohort-specific divorce levels by distorting other parameters. This motivates allowing divorce costs to differ across cohorts.

Despite these issues, Figures 1 and 2 show that the D model captures the broad patterns of marriage and divorce rates across cohorts remarkably well. The marriage rate age profiles are matched in levels and shape for all three cohorts, and—crucially—the divorce rate exhibits an age-declining pattern. The improvement in the divorce rate fit is the most visible consequence of age-dependent divorce costs.

5.3 The Baseline: Cohort-Specific Divorce Costs ($D{+}\omega$)

To resolve the identification problems of D, we allow the base level of divorce cost to differ across cohorts while retaining the age-dependent offsets. This adds 2 parameters to the estimation. Adolescents serve as the reference group ($\delta_a = 0$), and we estimate δ_y and δ_o. We thus have 21 parameters to be estimated.

The results are in the Baseline ($D{+}\omega$) column of Table 4. The WSSE falls to 0.056, a 16% reduction relative to D and a 72% reduction relative to Pooled. We designate this as our Baseline specification.

The estimated age offsets are $\delta_y = 2.50$ and $\delta_o = 0.31$. Young adults face the highest effective divorce cost, substantially above adolescents and the old. The effective divorce costs by maturity and cohort are shown in Table 5.

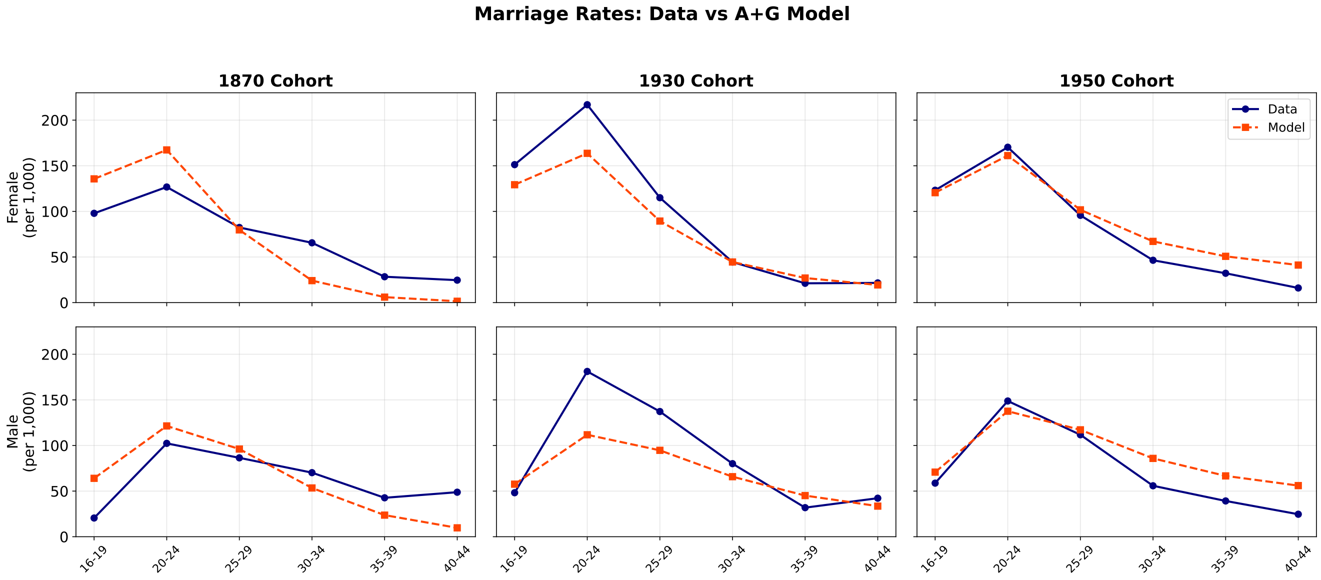

Figure 1. Marriage Rates in Data and D Model

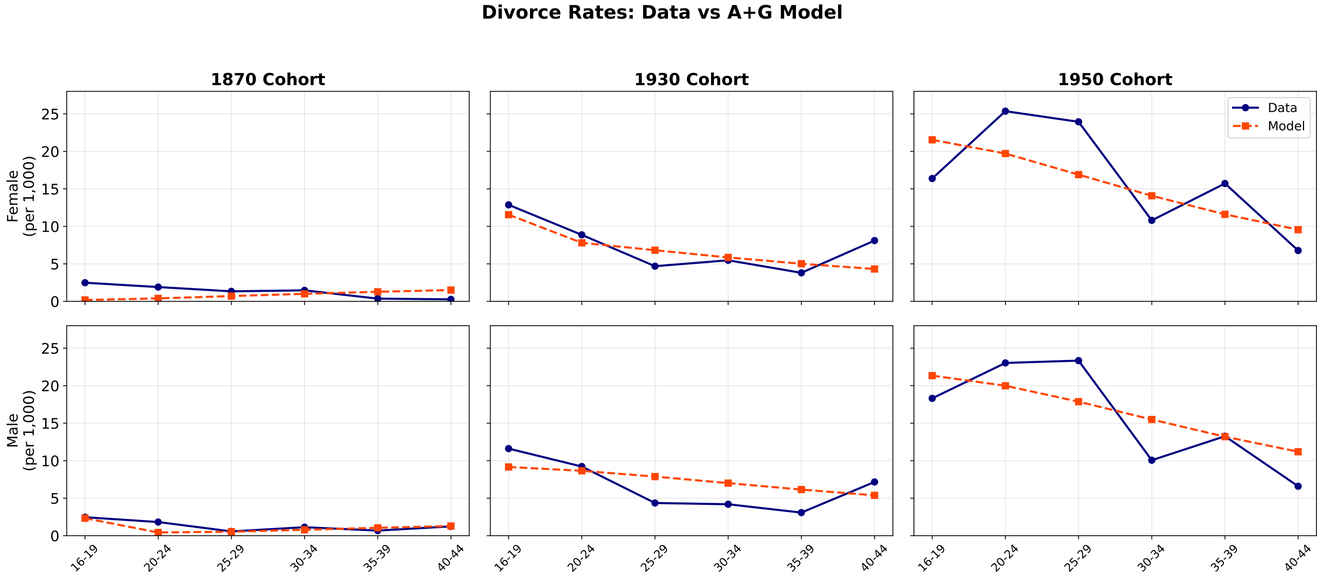

Figure 2. Divorce Rates in Data and D Model

Table 5. Effective Divorce Costs by Maturity and Cohort

	1870	1930	1950
Adolescent (ω)	13.18	5.30	2.17
Young ($\omega + \delta_y$)	15.68	7.80	4.67
Old ($\omega + \delta_o$)	13.49	5.61	2.48

The pattern is clear: young adults face the highest divorce cost across all cohorts. Without age-dependent costs, the model would predict a flat or even *rising* divorce rate with age, because older agents have less to gain from returning to the marriage market (shorter remaining lifetimes) and therefore tolerate worse matches—making divorce *less* attractive at older ages, not more. The age-dependent cost reverses this: it makes young adults reluctant to divorce despite their higher option value, generating the age-declining divorce rate profile observed in the data. The combination of high option value (which pushes toward divorce) and high divorce cost (which restrains it) at young ages produces the peak in divorce rates during young adulthood followed by decline.

We now provide a detailed discussion of the Baseline parameters, which constitute our preferred specification.

Preferences for partner maturity. Both sexes strongly dislike adolescent partners ($\alpha_a^f = -43.67$, $\alpha_a^m = -5.77$), though females penalize adolescent males far more heavily than males penalize adolescent females. This asymmetry is consistent with the observation that young women rarely marry teenage boys, whereas young men do occasionally marry teenage women. The most striking feature of the preference estimates is the large female preference for old males ($\alpha_o^f = 26.80$). Males are roughly indifferent between young and old females ($\alpha_y^m = 1.35$, $\alpha_o^m = -0.54$). Figure 3 displays these attractiveness profiles.

Aging process. Women become young adults at 18.4 and old at 26.7—the young adult period spans about 8 years. Men become young adults at 19.1 and old at 26.6, a similar pattern. Both sexes thus have their prime marriage years between roughly ages 18 and 27.

Match quality process. The gain from a good match ($\theta = 0.497$) is moderate. Once a match reaches the *H*-state, it is essentially permanent ($\Lambda_{HH} = 1.000$). The *M*-state transitions are heavily skewed toward deterioration: $\Lambda_{ML} = 0.83$ versus $\Lambda_{MH} = 0.17$. This means most marriages that start at medium quality deteriorate rather than improve. Once in the *L*-state, matches almost never improve ($\Lambda_{LL} = 0.992$). The process for love is thus quite pessimistic: most marriages either quickly become good and stay good, or deteriorate and remain bad, leading to divorce. The corner solution $\Lambda_{HH} = 1$ is a consequence of selection: marriages that survive the early period have revealed high match quality, and the data show very low divorce rates among longer-married couples. This is robust across all nine specifications—Λ_{HH} is at or near 1.00 in every case—suggesting it reflects a genuine feature of the data rather than a fragile parameter configuration.[9]

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[9] To verify this, we re-estimate the Baseline with Λ_{HH} bounded at 0.99 (i.e., a 1% annual probability that good matches deteriorate). The bound binds, and the WSSE increases by 12.5% (from 0.056 to 0.063). All other parameters are essentially unchanged (ω values shift by less than 0.08, δ_y by 0.04). The data strongly prefer permanent good matches; forcing even small deterioration carries a meaningful fit penalty without altering the remaining estimates.

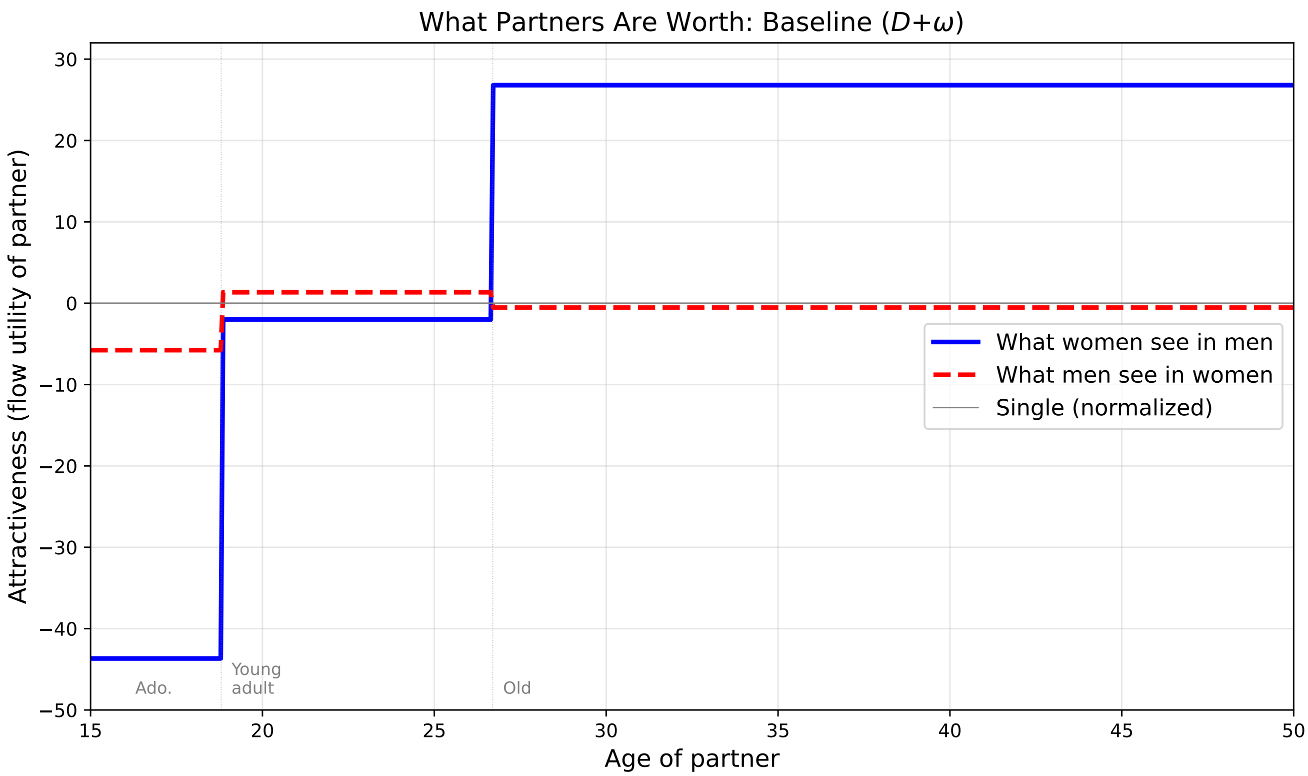

Figure 3. Partner Attractiveness by Age in the Baseline ($D+\omega$)

Notes: The step function reflects the model's three maturity stages. The sharp asymmetry—women strongly value older men, men are nearly indifferent to women's age—drives the marriage age gap.

Marriage and divorce costs. The marriage cost is 10.34. Divorce costs decline monotonically across cohorts (13.18, 5.30, 2.17), consistent with the secular decline in barriers to divorce. The 1950 cohort has the lowest base cost (2.17), but even this cohort faces a substantial effective divorce cost for young adults (4.7).

The key finding—age-dependent divorce cost. Young adults face the highest effective divorce cost (+2.50 above adolescents). This is consistent with several mechanisms: the accumulation of marriage-specific capital (children, shared housing, joint social networks, complementary career decisions), selection effects (young couples are more heterogeneous in match quality), or institutional features (property division is more complex for established households). The model does not distinguish among these channels, but the leading interpretation is marriage-specific investment: young adults are at the stage of life when couples make their largest joint investments, creating switching costs that make dissolution particularly expensive. By contrast, adolescent marriages—entered before these investments accumulate—and older marriages—where children have left and assets are established—involve lower dissolution costs. The small old-age offset (+0.31) confirms that most of the age-dependence comes from the young-adult peak rather than a gradual decline.

The monotone decline of the base divorce cost across cohorts is consistent with institutional changes that reduced the costs of dissolution: the liberalization of divorce laws (Voena, 2015), the growth of women's labor force participation (Regalia, Ríos-Rull, and Short, 2013), and the erosion of social stigma associated with divorce (Stevenson and Wolfers, 2007). Importantly, our estimates suggest that these secular changes affected the *level* of divorce cost uniformly, while the *age profile* of divorce cost—driven by life-cycle investment patterns—remained stable across cohorts.

Figures 4 and 5 display the fit of the Baseline. Compared to the D model (Figures 1 and 2), the addition of cohort-specific divorce cost levels brings the model closer to the data in two respects. First, the marriage rate levels are better calibrated across cohorts, particularly for the 1930 cohort where the D model over-predicted young male marriage. Second, the divorce rate profiles retain the age-declining pattern introduced by the age-dependent offsets while also matching the large cross-cohort differences in divorce levels—from near zero in the 1870 cohort to over 20 per thousand in the 1950 cohort.

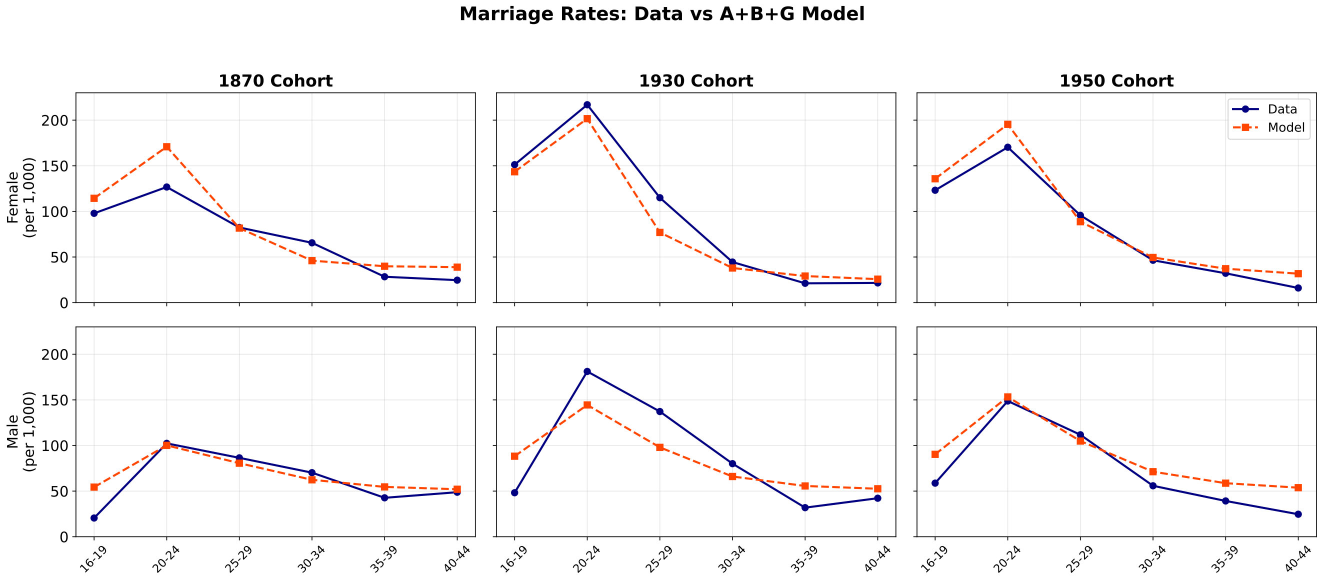

Figure 4. Marriage Rates in Data and Baseline ($D{+}\omega$)

Non-targeted moments. The model targets age-specific marriage and divorce *flow* rates but not marital *stock* fractions. The predicted fraction of the population that is married at any point in time (approximately 30%) falls short of the Census data (48–73%). This discrepancy arises because the model computes a stationary equilibrium, whereas the actual U.S. population is not in steady state: cohort-specific marriage and divorce rates applied to a stationary population yield lower marriage stocks than the transitional dynamics observed in the data. Similarly, the model overpredicts the crude

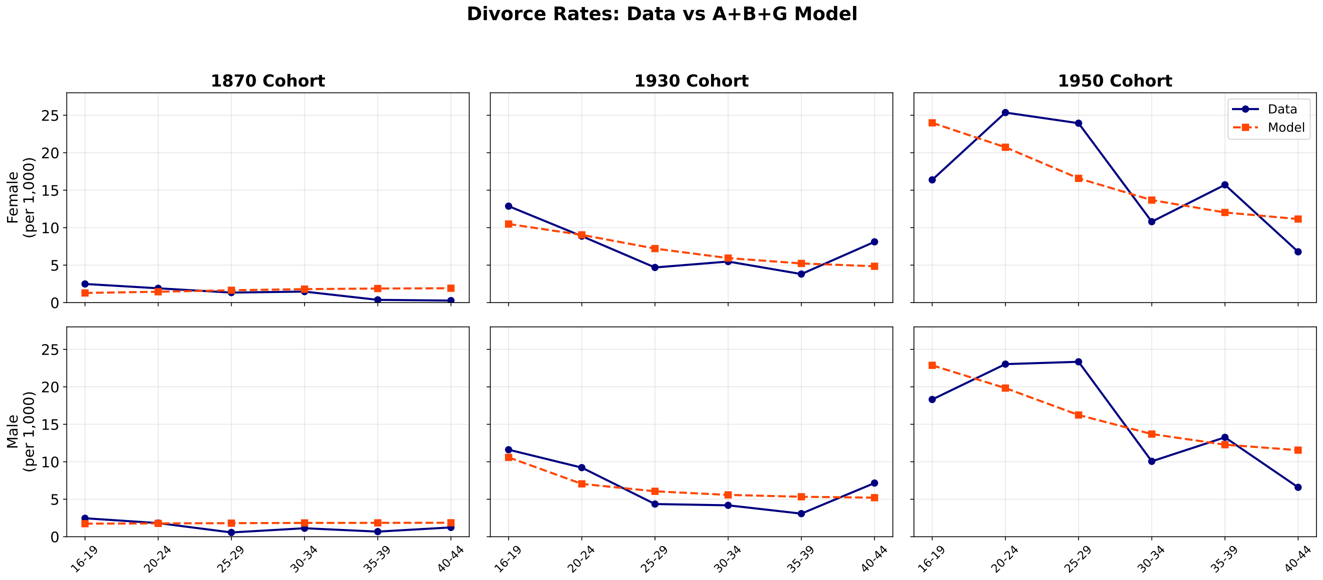

Figure 5. Divorce Rates in Data and Baseline ($D{+}\omega$)

aggregate divorce rate by a factor of approximately two, again reflecting the steady-state approximation. These discrepancies affect stock-based moments but not the flow rates that the estimation targets.

Out-of-sample validation: marriage survival. As an additional check on the model, we compare the implied probability that a marriage formed at age 20 survives to various horizons, using the estimated age-specific divorce rates. This duration profile is not directly targeted in estimation. Table 6 shows that the model closely tracks the data: for the 1870 cohort, the 20-year survival probability is 96.7% in the model versus 97.5% in the data. Even for the 1950 cohort, where divorce rates are much higher, the model captures the magnitude of marital dissolution (72.8% vs 68.2% at 20 years). The slight over-prediction of survival for the 1950 cohort is consistent with the model's difficulty matching the very high divorce rates at the youngest ages for this cohort.

5.4 Which Dimension of Divorce Cost Variation Matters?

The Baseline allows divorce costs to vary along two dimensions: across cohorts (three levels ω_c) and across maturities (two offsets δ_y, δ_o). We now ask which of these dimensions—and whether a third, sex—is the primary driver of the model's fit.

Age-dependence. To isolate the role of age-dependent costs, we estimate the model without them: the $D{+}\omega$ specification without age dependence allows demographics and divorce cost levels to differ across cohorts but forces the cost to be independent of the agent's maturity. The WSSE for this restricted specification is 0.087, some 55% worse than the Baseline's 0.056—despite having only 2

Table 6. Marriage Survival Probabilities: Data vs Model ($D+\omega$)

Cohort		Probability of surviving 5 years	10 years	15 years	20 years
1870	Data	0.990	0.984	0.977	0.975
	Model	0.993	0.985	0.976	0.967
1930	Data	0.956	0.934	0.909	0.892
	Model	0.956	0.922	0.895	0.871
1950	Data	0.879	0.779	0.738	0.682
	Model	0.901	0.828	0.773	0.728

Notes: Survival probabilities for a female married at age 20, computed from age-specific divorce rates. The duration profile is not targeted in estimation.

fewer parameters.

The estimated divorce costs under this restricted specification are monotonically declining across cohorts (13.45 for the 1870 cohort, 5.28 for the 1930 cohort, and 0.00 for the 1950 cohort). The zero cost for the 1950 cohort is a consequence of forcing a flat divorce cost profile: the model needs zero cost to generate the high divorce rates of this cohort, but this also removes any age variation in divorce.

Figure 6 illustrates the key difference. The restricted specification produces a nearly flat divorce rate profile across age groups for all cohorts, whereas the Baseline generates the pronounced age-declining pattern observed in the data. This improvement in the divorce rate fit is the primary channel through which age-dependent divorce costs reduce the WSSE.

Cohort variation. Cohort-specific divorce cost levels are clearly warranted: moving from D (common ω) to $D+\omega$ (cohort-specific ω_c) reduces the WSSE by 16%, from 0.067 to 0.056, with only 2 additional parameters. But this improvement is dwarfed by the 55% deterioration that results from removing age-dependence. Cohort variation in the *level* of divorce cost is important, but the *age profile* of divorce cost is the dominant feature.

Sex-specificity. We also investigate whether divorce costs differ between men and women by adding a single parameter δ_{sex} (male divorce cost premium) to the Baseline. Under this extension, the effective divorce cost for males is $\omega_c + \delta(i) + \delta_{\text{sex}}$ while females face $\omega_c + \delta(i)$, where c indexes the cohort and i the agent's maturity.

The estimated premium is $\hat{\delta}_{\text{sex}} = 0.42$, and the WSSE improves from 0.05661 to 0.05653—a reduction of less than 0.15%. With 22 parameters instead of 21, the adjusted WSSE (Equation (11))

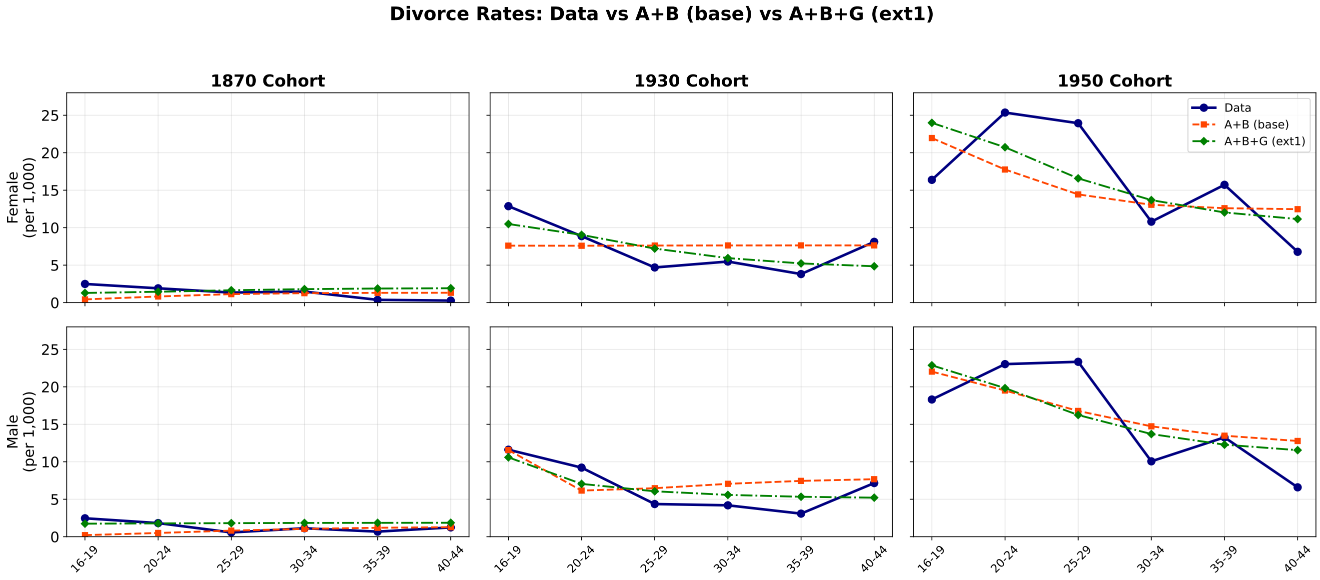

Figure 6. Divorce Rates: Data vs $D{+}\omega$ without age dependence vs Baseline ($D{+}\omega$)

actually worsens. The data thus provide no evidence that divorce costs differ between men and women, conditional on the age-dependent structure already in the model. We retain symmetric divorce costs in all specifications that follow.

Summary. Age-dependence in divorce costs wins by a wide margin. The two age offsets (δ_y, δ_o) reduce the WSSE by 36% relative to a model without them. Adding a sex dimension buys less than 0.15%. Cohort variation in divorce cost levels is valuable but secondary. The hierarchy is clear: age $\gg$ cohort $\gg$ sex.

6 Cohort-Specific Parameter Variation: A Horse Race

6.1 Which Parameters Change Across Cohorts?

Having established the Baseline, we now ask: beyond divorce costs, which behavioral parameters differ most across cohorts? We estimate six specifications, each allowing a different subset of parameters to vary by cohort while retaining cohort-specific demographics and divorce costs. Table 7 reports the results.

The WSSE values respect the expected ordering: Full $< D{+}\omega{+}\alpha{+}\Gamma < D{+}\omega{+}\lambda < D{+}\omega{+}\Gamma < D{+}\omega{+}\alpha <$ Baseline, with WSSE values ranging from 0.041 (Full, everything varies, 53 parameters) to 0.056 (Baseline, 21 parameters). Each additional group of cohort-specific parameters yields a

Table 7. Estimated Parameters for Various Specifications with Age-Dependent Divorce Costs, 1870-1930-1950

Version of the Model Parameters that Differ		D+ω+α (A+C+G)			D+ω+Γ (A+D+G)			D+ω+λ (A+E+G)			D+ω+ϕ (A+F+G)			D+ω+α+Γ (A+C+D+G)			Full (All+G)	
Cohort	1870	1930	1950	1870	1930	1950	1870	1930	1950	1870	1930	1950	1870	1930	1950	1870	1930	1950
(C) Preferences																		
α_a^f	-157.18	-46.38	-40.02		-13.68			-6.63			-125.68		-979.55	-62.45	-148.24	-3.43	-7.56	-25.18
α_a^m	-4.51	-3.99	-6.04		-38.77			-230.00			-978.06		-4.93	-4.04	-10.82	-221.39	27.12	-457.80
α_y^f	-16.00	9.34	-0.81		-0.56			-0.85			9.38		-22.63	15.12	0.23	-1.25	-0.41	0.09
α_y^m	0.97	2.70	1.04		17.54			-34.05			-1.16		1.23	2.85	0.64	-11.99	-2.07	-47.95
α_o^f	113.31	67.04	12.05		-3.21			-2.08			73.67		280.52	48.40	39.26	-2.50	-2.18	-2.27
α_o^m	-0.71	-0.44	-0.81		2.35			147.67			-2.24		-0.64	-0.49	-0.80	189.06	190.00	141.10
(D) Aging process																		
Females																		
Becoming young		19.2		18.7	18.3	18.6		17.2			17.3		19.7	19.2	18.6	17.1	17.7	17.3
Becoming old		26.7		29.8	30.3	32.2		42.6			39.8		25.1	25.3	27.9	51.0	37.6	38.1
Males																		
Becoming young		19.4		21.5	19.3	18.7		18.2			18.2		20.6	18.9	18.8	19.7	18.7	18.2
Becoming old		27.6		34.6	26.3	31.2		56.0			51.8		30.2	29.2	28.5	62.7	39.6	36.6
(F) Marriage cost (ϕ)		9.20			7.50			21.01		16.41	8.44	13.02		8.45		24.96	18.54	16.98
(E) Match quality																		
Gain in H-state (θ)		0.52			4.16		1.94	3.91	3.89		2.29			0.55		0.97	3.36	3.64
Prob. $L \to L$ (Λ_{LL})		1.00			0.39		1.00	1.00	0.84		0.95			1.00		1.00	1.00	0.84
Prob. $M \to H$ (Λ_{MH})		0.80			0.65		0.97	0.91	0.44		0.75			0.80		0.97	0.89	0.47
Prob. $M \to L$ (Λ_{ML})		0.20			0.32		0.03	0.07	0.17		0.25			0.20		0.03	0.09	0.16
Prob. $H \to H$ (Λ_{HH})		1.00			1.00		1.00	1.00	1.00		1.00			1.00		1.00	1.00	1.00
(B) Divorce cost (ω)	15.03	11.55	2.70	9.88	5.40	2.30	31.74	0.02	15.62	23.61	31.25	13.03	15.68	12.77	2.82	43.07	0.00	11.36
(G) Age-dep. divorce (δ_y)		2.52			3.50			2.55			2.05			2.09			4.25	
(G) Age-dep. divorce (δ_o)		0.51			-0.71			-1.47			0.65			0.46			-1.00	
WSSE		0.052			0.050			0.048			0.053			0.046			0.041	
AWSSE		0.086			0.076			0.076			0.073			0.090			0.111	
% reduction		74%			75%			76%			74%			77%			80%	
Num. params		33			29			31			23			41			53	

meaningful improvement. The most informative comparison is among the single-channel extensions ($D+\omega+\alpha$ through $D+\omega+\phi$), which each add one behavioral channel (Table 8):

Table 8. Single-Channel Extensions: WSSE Comparison Across Specifications

Specification	What varies (beyond Baseline)	# par	WSSE	% below Baseline
Baseline ($D+\omega$)	—	21	0.056	—
$D+\phi$ (new)	Marriage cost ϕ instead of ω	21	0.077	−37%
$D+\lambda$ (new)	Match quality instead of ω	29	0.056	0%
$D+\omega+\phi$	+ marriage cost ϕ	23	0.053	6%
$D+\omega+\alpha$	+ preferences α	33	0.052	7%
$D+\omega+\Gamma$	+ aging $\bar{\Gamma}$	29	0.050	10%
$D+\omega+\lambda$	+ match quality Λ, θ	31	0.048	14%
$D+\omega+\alpha+\Gamma$	+ preferences + aging	41	0.046	18%
Full	+ everything	53	0.041	27%

Match quality variation ($D+\omega+\lambda$) yields the largest single-channel gain—14% below the Baseline—followed by aging (10%), preferences (7%), and marriage cost (6%). To confirm that divorce cost variation (ω) dominates marriage cost variation (ϕ), we estimate $D+\phi$, which replaces cohort-specific ω with cohort-specific ϕ at the same parameter count (21). $D+\phi$ achieves only WSSE $= 0.077$, 37% *worse* than the Baseline. The secular decline in marital commitment (falling ω) is thus a far more important cohort variation than changes in the barriers to entering marriage.

Divorce costs are typically monotone. Across the Baseline through $D+\omega+\Gamma$, the base divorce cost declines monotonically ($\omega_{1870} > \omega_{1930} > \omega_{1950}$), with ω_{1870} ranging from 9.9 to 15.0 and ω_{1950} between 2.2 and 2.7. The exceptions ($D+\omega+\lambda$ and $D+\omega+\phi$, plus the Full), cohort variation in other channels absorbs the divorce-cost variation. This substitutability between match quality dynamics and divorce costs is economically informative: both channels govern marital dissolution, and the data cannot sharply separate their contributions in all specifications.

What changes in preferences ($D+\omega+\alpha$)? The preference changes are driven entirely by women. Women's premium for older over younger men collapses monotonically across cohorts: $\alpha_o^f - \alpha_y^f =$ 129 (1870), 58 (1930), 13 (1950). To put this in perspective, 129 is more than 100 times the standard deviation of the transitory match shock: in the 1870 cohort, the age of a prospective husband dominates all other match-specific considerations. By 1950, age barely matters relative to idiosyncratic compatibility. Male preferences over partner age are essentially constant across all three cohorts (α_y^m ranges from 1.0 to 2.7). This tracks women's rising labor force participation: as women's own earnings grow, the value of an older, more established male provider diminishes.

What changes in aging ($D+\omega+\Gamma$)? The aging changes are driven entirely by men. Men's expected duration in the "adolescent" stage falls monotonically: 5.5 years (1870), 3.3 years (1930), 2.7 years (1950). Women's youth duration is stable (2.7–2.3 years). The gender gap in maturation timing closes from 2.8 years to essentially zero, tracking the closing of the education gap and the rise of dual-earner households. In the 1870 cohort, men take substantially longer than women to become "marriageable"; by 1950, both sexes mature at similar rates, compressing the gender gap in age at first marriage.

What changes in match quality ($D+\omega+\lambda$)? Match quality dynamics exhibit two monotone trends across all three cohorts. First, the probability that a medium-quality match improves to high quality ($M \to H$) falls steadily: 0.97 (1870), 0.91 (1930), 0.44 (1950). Second, the probability that a medium-quality match deteriorates ($M \to L$) rises: 0.03, 0.07, 0.17. Medium matches become progressively more fragile. In the 1870 and 1930 cohorts, patience is rewarded—medium matches almost always improve—and divorce is rare because bad outcomes are rare. The 1950 cohort is qualitatively different: medium matches are roughly a coin flip (44% improve, 17% worsen, 39% stay), and—uniquely—bad matches can now recover ($L \to M = 0.16$), generating cohabitation-like dynamics in which couples can "try again" after a bad spell. The stakes of match quality also increase (θ roughly doubles from 1.9 to 3.9), so the spread between good and bad matches widens. Combined with fragile medium matches, this produces more selective entry: agents wait longer for quality signals before committing, pushing up age at first marriage. The implied expected time for a new marriage to reach the good state rose from about 1 year (1870) to over 2 years (1950)—a doubling of the "trial period" that maps directly onto the observed rise in early-marriage divorce.

Decomposition from the Full specification. Starting from the Full specification and constraining each group to be shared one at a time, we measure the marginal contribution of cohort variation in each channel. Divorce cost variation is indispensable: forcing shared ω raises WSSE from 0.041 to 2.092. Match quality is the most important behavioral channel (ΔWSSE $= +0.995$), followed by aging ($+0.703$), preferences ($+0.300$), and marriage cost ($+0.174$). This ranking is consistent with the single-group extensions above and confirms that match quality dynamics are the primary behavioral dimension along which cohorts differ.

Divorce costs and match quality are substitutes. To sharpen the comparison between these two leading channels, we estimate $D+\lambda$, which allows match quality to vary across cohorts but *shares* the base divorce cost ω (no cohort-specific levels). This specification has 29 parameters and achieves WSSE $=$ 0.056—identical to the Baseline, which achieves the same fit by allowing ω to vary while sharing match quality. The three-way comparison is shown in Table 9:

Table 9. Substitutability of Divorce Costs and Match Quality

Specification	What varies by cohort	# par	WSSE
Baseline ($D+\omega$)	demographics + ω	21	0.056
$D+\lambda$	demographics + match quality (Λ, θ)	29	0.056
$D+\omega+\lambda$	demographics + ω + match quality	31	0.048

The Baseline and $D+\lambda$ achieve the same goodness of fit through different mechanisms: one explains cross-cohort variation in marital patterns through declining divorce costs, the other through evolving match quality dynamics. At the level of fit achievable with a single behavioral channel, the two are perfect substitutes. This is not a statistical coincidence but an economic insight: both channels govern marital dissolution—divorce costs affect the *price* of exit, while match quality dynamics affect the *probability* of wanting to exit—and the data cannot distinguish between them when only one is allowed to vary.

When *both* channels are allowed to vary ($D+\omega+\lambda$), the fit improves to 0.048—a further 14% reduction. This gain reveals that the two channels capture genuinely different dimensions of social change: declining divorce costs capture the liberalization of exit (legal, social), while evolving match quality captures changes in how relationships form and persist (cohabitation, selectivity, fragility). The Baseline is more parsimonious (21 vs. 31 parameters), but $D+\omega+\lambda$ captures variation that ω alone cannot reach.

6.2 Counterfactual Decompositions

Having established which parameters change most, we now ask how much each channel contributes to the observed cross-cohort differences. We use the Baseline estimates ($D+\omega$) to conduct counterfactual exercises that decompose the sources of changing marital patterns. Each exercise modifies one set of inputs—demographics, divorce cost levels, or age-dependent divorce cost offsets—while holding all other parameters at their estimated values, and solves for the new equilibrium. Full results are in Online Appendix J.

Decomposing demographics: sex ratios vs. longevity. The large demographic effect documented in Section 5.2 (0.201 → 0.067) reflects two forces: the reversal of the sex ratio from a 5.6% male surplus (1870) to a 5.8% female surplus (1950), and the increase in life expectancy (+15 years for women, +11 for men) with a widening gender gap (0.7 to 7.3 years). To separate these, we give all cohorts the 1870 sex ratio while keeping their own life expectancies (CF-A), or the 1870 life expectancies while keeping their own sex ratios (CF-B). The two channels matter differently for different cohorts. For the 1930 cohort, the sex ratio is the dominant demographic force (ΔWSSE $= +0.048$ vs. $+0.019$ for longevity): the shift from male surplus to female surplus reshapes who marries whom. For the 1950 cohort, longevity dominates (ΔWSSE $= +0.067$ vs. $+0.006$): longer lives and the widening gender gap alter divorce patterns and the marriage market at older ages. The interaction is sub-additive ($+0.078 < 0.048 + 0.067 = 0.115$ for the combined effect), indicating that sex ratios and longevity partially substitute for each other in shaping marriage market equilibria.

Demographics swap. We assign the 1950 cohort the demographic environment of the 1870 cohort (sex ratio and mortality rates) while retaining the 1950 estimated divorce costs and all preference parameters. The shift from female surplus back to male surplus reduces male marriage rates by 2–4 percentage points at ages 20–29, as males become the abundant sex and face more competition. Female never-married rates fall by 3 percentage points as women become the scarce sex. Divorce rates for young women fall substantially (from 2.4% to 1.1% at ages 16–19), as the higher value of marriage under favorable demographics makes couples less willing to dissolve. Demographics thus account for a meaningful share of cross-cohort differences in marriage market outcomes, but they cannot explain the rise in divorce—the 1870 demographic environment actually *raises* overall divorce rates for males, reflecting the complex general equilibrium interactions between sex ratios and matching.

Divorce cost equalization. We assign all three cohorts the 1870 divorce cost level ($\omega_{1870} = 13.18$) while retaining their own demographic environments. The effect is dramatic: the aggregate divorce rate for the 1950 cohort falls from 12.5 to 2.7 per thousand—a 78% reduction—essentially returning it to 1870-era levels. For the 1930 cohort, the aggregate divorce rate falls by half. Divorce rates for young women in the 1950 cohort drop from 2.4% to 0.5% at ages 16–19, and from 2.1% to 0.4% at ages 20–24. The decline in divorce costs across cohorts is thus the dominant force behind the secular rise in divorce. Marriage rates also respond: with higher divorce costs, fewer marriages form because agents anticipate that bad matches will be harder to exit.

Removing age-dependence in divorce costs. We set $\delta_y = \delta_o = 0$, removing the age-dependent component of divorce costs while retaining the cohort-specific levels. The effect is catastrophic for the model's predictions. Without the high divorce cost for young adults, the marriage market essentially collapses: never-married rates at age 50 explode from 7–11% to 40–85%, and marriage rates at ages 20–24 fall by 10–16 percentage points. Divorce rates become flat or increasing in age, the opposite of the data pattern. This exercise confirms that age-dependent divorce costs are not merely a statistical improvement but a structurally essential feature: they sustain the marriage market by making early unions durable enough to justify the cost of entry.

Gender-neutral preferences. We impose symmetric preferences by setting $\alpha_i^f = \alpha_i^m = (\alpha_i^f + \alpha_i^m)/2$ for each maturity $i \in \{a, y, o\}$, so that men and women value partner age identically. The effect on marriage timing is striking: female age at first marriage rises by 6–10 years (from 21–22 to 29–31), as women no longer strongly penalize adolescent males ($\alpha_a^f = -43$ becomes -25) and no longer favor old males ($\alpha_o^f = 27$ becomes 13). Marriage rates for women at ages 16–24 collapse by 10–16 percentage points, while marriage rates at ages 35–44 nearly triple. The overall pattern shifts from sex-differentiated timing—where women marry young and men marry slightly later—to uniformly delayed marriage for both sexes. This confirms that gender-specific preferences over partner maturity are a first-order determinant of the observed marriage age gap and the concentration of female marriage at young ages.

Sex-specific marriage costs. We explore whether making the cost of marriage sex-specific would meaningfully change marriage patterns, by adding $+5$ to either the male or female marriage cost (a 50% premium relative to $\phi = 10.3$). The effects are dramatically asymmetric. When males face higher marriage costs, never-married rates for both sexes explode to approximately 50%, and marriage rates at all ages drop by half. When females face higher costs, the effect is reversed and more moderate: marriage rates actually rise for young males while never-married rates fall to near zero. This asymmetry reflects the general equilibrium nature of the marriage market—making one side more reluctant to marry does not simply reduce marriages proportionally, but reshapes the entire equilibrium through changes in competition, selectivity, and the value of waiting. The fact that the Baseline estimates a common marriage cost is thus a substantive finding, not merely a normalization.

7 Out-of-Sample Exercises

We evaluate the model's out-of-sample predictive power by applying the Baseline estimates ($D+\omega$) to two cohorts not used in estimation: the 1910 birth cohort, which falls between the two earliest estimation cohorts, and the 1970 birth cohort, which extends well beyond the estimation sample. For each cohort we construct demographic inputs and marriage/divorce moments from the same IPUMS Census microdata and stock-to-flow methodology used for the estimation cohorts (see Online Appendix A). These two exercises serve very different purposes. The 1910 cohort tests whether the model can interpolate within the institutional environment of the estimation sample. The 1970 cohort asks whether the model's mechanisms can extrapolate to an era of profound social change.

7.1 Validation: The 1910 Cohort

The 1910 cohort lived in a marriage market with a sex ratio of 0.977 men per woman (from the 1940 Census), intermediate between the 1870 cohort (1.056) and the 1930 cohort (0.952), with life expectancy at age 15 of 60.5 years for women and 54.4 years for men. We hold all Baseline preference, match quality, and age-dependent divorce cost parameters (δ_y, δ_o) at their estimated values and search over the base divorce cost ω to find the value that best fits the 1910 cohort's 28 marital moments.

The estimated divorce cost is $\hat{\omega}_{1910} = 13.00$, essentially identical to the 1870 value ($\omega_{1870} = 13.18$). The model fits the 1910 cohort remarkably well: the cohort-specific WSSE is 0.017, lower than any of the three in-sample cohorts. Table 10 reports the fit. Age at first marriage is matched almost exactly (21.6 vs. 21.6 for females, 24.6 vs. 24.6 for males), and the never-married fractions are within one percentage point. The model over-predicts marriage rates at ages 16–24 and under-predicts them at ages 30–34, a pattern consistent with the Depression-era marriage delay that affected this cohort at those ages.

The finding that $\omega_{1910} \approx \omega_{1870}$ is historically informative. The decline in divorce costs did not begin gradually in the late nineteenth century; instead, divorce costs remained at their historical level through the 1910 cohort and then dropped sharply for the 1930 cohort ($\omega_{1930} = 5.30$). The full trajectory is

$$\omega_{1870} = 13.18 \;\rightarrow\; \omega_{1910} = 13.00 \;\rightarrow\; \omega_{1930} = 5.30 \;\rightarrow\; \omega_{1950} = 2.17,$$

suggesting a structural break between the 1910 and 1930 cohorts, coinciding with the post–World War I social transformation, the expansion of legal grounds for divorce, and the beginning of women's entry into the labor force. A log-linear regression of $\ln \omega_c$ on cohort year, fit to the three in-sample cohorts (1870, 1930, 1950) and extrapolated to 1970, predicts $\omega_{1970} = 1.75$, close to the cohort-specific estimate of 1.55 obtained in Section 7.2—indicating that the 1970 divorce cost is consistent with the in-sample trend rather than requiring a further structural break.

7.2 Social Change: The 1970 Cohort

The 1970 cohort presents a much harder test. Its sex ratio is 0.989 men per woman (from the 2000 Census)—nearly balanced—and life expectancy at age 15 is approximately 66.5 years for women and 61.5 years for men. Because the 1970 cohort has not yet reached age 50, we approximate the never-married fractions at 15% (female) and 20% (male) based on ACS trends; the remaining 26 moments

Table 10. Out-of-Sample Fit: 1910 Birth Cohort ($\hat{\omega}_{1910} = 13.00$)

	Female			Male		
Age group	Data	Model	WSE	Data	Model	WSE
Marriage rates						
16–19	0.108	0.143	0.0012	0.031	0.078	0.0022
20–24	0.142	0.200	0.0035	0.119	0.133	0.0002
25–29	0.094	0.073	0.0004	0.121	0.094	0.0007
30–34	0.086	0.034	0.0027	0.106	0.066	0.0017
35–39	0.035	0.028	0.0001	0.063	0.056	0.0001
40–44	0.040	0.026	0.0002	0.041	0.052	0.0001
Divorce rates						
16–19	0.011	0.005	0.0032	0.009	0.009	0.0000
20–24	0.006	0.004	0.0002	0.005	0.006	0.0001
25–29	0.004	0.004	0.0001	0.004	0.004	0.0001
30–34	0.005	0.003	0.0003	0.003	0.003	0.0000
35–39	0.003	0.003	0.0000	0.004	0.003	0.0001
40–44	0.002	0.002	0.0000	0.001	0.002	0.0001
Summary moments						
Age 1st marriage		21.6 → 21.6			24.6 → 24.6	
Never married, 50		7.5% → 7.9%			7.2% → 7.5%	
Cohort WSSE						0.017

are computed from Census data through 2010.

The Baseline prediction fails. We first ask what the model predicts using 1970 demographics and the 1950 divorce cost ($\omega_{1950} = 2.17$). The prediction fails dramatically: the model generates marriage rates 2–5 times higher than the data at ages 16–24, predicts age at first marriage of 22.3 (vs. 24.3 in the data for females) and 23.3 (vs. 26.9 for males), and predicts never-married rates of 5–6% versus the observed 15–20%. Estimating a cohort-specific ω_{1970} yields $\hat{\omega}_{1970} = 1.55$, continuing the declining trend, but the fit remains poor (cohort WSSE = 0.101, six times the 1910 value). Even jointly varying the marriage cost (ϕ) alongside ω produces only modest improvement: the best-fitting pair is $\phi = 10.8$, $\omega = 1.25$ with WSSE = 0.093.

Table 11. The 1970 Birth Cohort: Baseline Prediction vs. Cohort-Specific Estimation

		Baseline ($\hat{\omega}$ only)		Cohort-specific	
	Data	Female	Male	Female	Male
Marriage rates					
16–19		0.141	0.108	0.064	0.041
20–24		0.206	0.179	0.115	0.082
25–29		0.100	0.117	0.092	0.072
30–34		0.061	0.077	0.060	0.054
Data targets					
16–19		0.047	0.022	0.047	0.022
20–24		0.110	0.082	0.110	0.082
25–29		0.100	0.096	0.100	0.096
30–34		0.054	0.058	0.054	0.058
Summary moments					
Age 1st marriage		21.9	23.0	24.7	26.8
Data		24.3	26.9	24.3	26.9
Never married, 50		5.4%	4.5%	14.4%	18.4%
Data		15.0%	20.0%	15.0%	20.0%
Cohort WSSE		0.101		0.012	

The model failure is about parameter values, not model structure. The pattern of Baseline failure—marriage rates far too high at ages 16–24, never-married fractions of 5% versus the observed 15–20%—points to delayed and more selective entry into marriage, not merely easier exit. Adjusting divorce costs (ω, ϕ) alone cannot resolve this because lower divorce costs encourage *more* early marriages (bad matches are cheap to exit), exactly the opposite of the 1970 pattern. Even jointly varying ϕ and ω yields only modest improvement (WSSE = 0.093).

We therefore re-estimate the full parameter vector for the 1970 cohort, using the joint estimates as a starting point. The cohort-specific estimation achieves WSSE $= 0.012$—comparable to the 1910 out-of-sample exercise and roughly one-fifth of the baseline prediction error. Table 11 compares the two fits. The cohort-specific model matches age at first marriage to within 0.4 years for females and 0.1 years for males, and predicts never-married fractions of 14.4% (female) and 18.4% (male) versus the data targets of 15% and 20%.

Which parameters carry social change? Table 12 reports the parameter shifts that achieve this fit. Three channels account for most of the improvement:

Table 12. Parameter Changes: Joint Estimate vs. 1970 Cohort-Specific

Parameter	Joint (Baseline)	1970-specific	Interpretation
$\bar{\Gamma}_{f,12}$ (cgf1)	0.36	1.53	Later female young→middle transition
$\bar{\Gamma}_{m,12}$ (cgm1)	0.76	1.54	Later male young→middle transition
θ	0.50	0.64	Higher match quality (selective entry)
Λ_{HH}	-19.5	-10.8	Less persistent good matches
ω_{1970}	2.17	1.70	Lower divorce cost
ϕ	10.31	9.77	Slightly lower marriage cost
$\alpha_{f,a}$	-43.0	-49.4	Stronger female age-sensitivity

1. *Later aging transitions.* The aging parameters $\bar{\Gamma}_{f,12}$ and $\bar{\Gamma}_{m,12}$, which govern the transition from "young" to "middle-aged," shift upward by roughly one full unit for both sexes. This is the single most important channel: in a grid search over two-parameter combinations, ω plus aging shift alone reduces the WSSE from 0.101 to 0.054. The shift is consistent with lengthening educational attainment and delayed household formation: if the 1970 cohort's effective "young adult" period extends several years beyond the estimation sample's, the model naturally delays marriage entry.

2. *More selective matching.* The match-quality parameter θ rises from 0.50 to 0.64, implying that marriages that do form are better matches on average. This is consistent with the 1970 cohort's higher educational attainment and the availability of cohabitation as a low-commitment alternative: agents can afford to wait for better partners.

3. *Less persistent match quality.* The love-persistence parameter Λ_{HH} moves from -19.5 to -10.8, raising the probability that a high-quality match transitions to medium quality. Under the Baseline value, good matches are essentially permanent ($H \to M$ probability ≈ 0); the 1970-specific value

implies a small but positive transition probability, consistent with rising expectations and the normalization of divorce.

Notably, the marriage cost ϕ *falls* slightly rather than rising, and the divorce cost $\omega_{1970} = 1.70$ is close to but above the grid-search optimum of 1.5. The delay in marriage for the 1970 cohort is driven primarily by later maturation and pickier matching, not by higher entry barriers.

Interpretation. The contrast is clear: the 1910 cohort can be matched with demographics and a single divorce cost, while the 1970 cohort requires parameter shifts—later aging, selective matching, fragile unions—that map onto well-documented social changes (lengthening education, cohabitation, divorce normalization). The 1970 exercise reveals that generational change after 1950 cannot be reduced to declining divorce costs alone.

Connection to the in-sample horse race. The three channels identified by the 1970 exercise align precisely with the in-sample horse race of Section 6.1. Match quality dynamics yield the largest in-sample gain ($D{+}\omega{+}\lambda$, 14% below Baseline), and the 1970 estimation confirms that match quality is the dimension along which this cohort differs most: medium matches become far more fragile, and the stakes of match quality (θ) rise. Aging transitions—the second-largest in-sample channel ($D{+}\omega{+}\Gamma$, 10%)—map onto the 1970 cohort's delayed maturation. The coherence between in-sample (1870–1950) and out-of-sample (1970) rankings strengthens the economic interpretation: the model is not merely fitting noise in the estimation cohorts, but identifying genuine behavioral dimensions along which successive generations differ.

Identification caveat: preference parameters. The 1970 cohort-specific estimation reveals a flat direction in the objective function over the preference parameters α_o^f and α_o^m. Independent runs from different starting points converge to very different values of these parameters (e.g., α_o^f ranges from -49 to $+113$ across runs) while achieving the same WSSE to four decimal places. This is not surprising: with a single cohort and no cross-cohort variation in α, the level of preferences is only weakly identified by the age profile of marriage rates. For the in-sample estimation (1870–1950), cross-cohort variation provides additional identifying power, and the Baseline preference parameters are precisely estimated (all $t > 4$ except α_a^m; see Online Appendix C). The flat direction in 1970 does not affect the estimates of aging, match quality, or divorce cost parameters, which are robust across starting points. It does, however, counsel caution in interpreting the 1970-specific preference values in Table 12 as point estimates rather than as representative members of an equivalence class.

8 Conclusion

Much of the long-run change in U.S. marriage and divorce behavior reflects shifting demographics, not changing preferences. We have used the variation in sex ratios and age composition across birth cohorts to estimate a general equilibrium model of marriage and divorce. The model matches 84 moments of marriage and divorce behavior across three cohorts (1870, 1930, 1950), identifies age-specific marriage preferences, match quality dynamics, and the costs of marriage and divorce.

Five findings emerge from the estimation.

First, demographics do the heavy lifting. Sex ratios and mortality variation alone explain 67% of cross-cohort differences in marriage and divorce patterns (0.201 → 0.067), with no behavioral parameters varying across cohorts. The sex ratio reversal (from male surplus to female surplus) is the dominant demographic force for the 1930 cohort, while the increase in longevity and its widening gender gap dominate for the 1950 cohort.

Second, divorce costs must vary across cohorts. Allowing a cohort-specific divorce cost adds a further 16% improvement with just 2 extra parameters. The decline is monotone and steep: $\omega_{1870} = 13.18 \rightarrow \omega_{1950} = 2.17$, a six-fold reduction. Marriage frictions are a poor substitute for divorce costs. The decline is robust across specifications and to alternative weighting matrices, and all pairwise differences are statistically significant ($t > 6$).

Third, match quality dynamics are the main behavioral dimension of generational change. A horse race across four channels reveals that the cohort-specific match quality process yields the largest gain (14%), followed by aging (10%), preferences (7%), and marriage frictions (6%). The changes have clear economic content: medium-quality matches become monotonically more fragile across cohorts ($M \rightarrow H$ falls from 97% to 44%, $M \rightarrow L$ rises from 3% to 17%), while the stakes of match quality (θ) roughly double. In preferences, the change is driven entirely by women—their premium for older husbands collapses from 129 to 13 points—while male preferences are constant. In aging, the change is driven entirely by men—their expected time as "young adults" falls from 5.5 to 2.7 years, converging toward women's.

Fourth, divorce costs and match quality are substitutes. Cohort-specific match quality alone (without cohort-specific ω) achieves the same fit as the Baseline. Both channels govern marital dissolution—one via the price of exit, the other via the probability of wanting to exit—and the data cannot distinguish between them when only one is allowed to vary. But combining both yields a further 14% gain, revealing that the two channels capture genuinely different dimensions of social change: the liberalization of exit (declining ω) and the evolving nature of relationships (fragile matches, selective entry).

Fifth, the model validates out of sample. The 1910 birth cohort is predicted remarkably well (WSSE $= 0.017$, better than any in-sample cohort), with an estimated divorce cost essentially identical to the 1870 value—confirming another structural break between 1910 and 1930. The 1970 cohort cannot be matched with demographics and divorce costs alone (WSSE $= 0.101$), but full re-estimation achieves WSSE $= 0.012$, and the required parameter shifts—later aging, more selective matching, more fragile unions—are precisely the channels that the in-sample horse race identifies as most important. This coherence between in-sample and out-of-sample rankings strengthens the economic interpretation.

A central finding that cuts across all specifications is that the cost of divorce depends on the agent's maturity. Young adults face the highest divorce cost ($\delta_y = 2.50$), generating the age-declining divorce rate profile observed in the data. Removing age-dependence causes the marriage market to collapse. We interpret this as reflecting the accumulation of marriage-specific capital during young adulthood: children, shared housing, joint social networks, and complementary career decisions create switching costs that make dissolution particularly expensive at that life stage.

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Online Appendix to “What Women See in Men and Vice Versa: Estimates Based on Sex Ratios and Marriage Patterns”

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A Data Construction and Sources

In this appendix, we describe how we construct marriage and divorce rates (flow variables) from the fractions of the population by age and marital status (stock variables). We observe only stock variables in the U.S. Census data, while we use flow variables in our estimation.[1] The methodology described below applies uniformly to all five birth cohorts—the three estimation cohorts (1870, 1930, 1950) and the two out-of-sample cohorts (1910, 1970). All computations use the same IPUMS Census microdata extract, which includes full-count and sample censuses from 1850 through 2010. We also list all the data sources for the variables we use.

A.1 Constructing Marriage and Divorce Rate from the Census Data

Denote the stock of females at calendar age t who are never-married, married, divorced, and widowed by S_t^f, M_t^f, D_t^f, and W_t^f, respectively. Denote $p_{m,t}^f$ the probability a single female of calendar age t gets married, and $p_{d,t}^f$ the probability a married female of calendar age t gets divorced. Then, the stocks in each marital state evolve over time according to the following equations:

$$\begin{aligned}
S_{t+1}^f &= S_t^f \left(1 - p_{m,t}^f\right)\left(1 - \pi_t^f\right), &(1)\\
M_{t+1}^f &= M_t^f \left(1 - p_{d,t}^f\right)\left(1 - \pi_t^m\right)\left(1 - \pi_t^f\right) + \left(S_t^f + D_t^f + W_t^f\right) p_{m,t}^f, &(2)\\
D_{t+1}^f &= M_t^f \left(1 - \pi_t^f\right)\left(1 - \pi_t^m\right) p_{d,t}^f + D_t^f \left(1 - \pi_t^f\right)\left(1 - p_{m,t}^f\right), &(3)\\
W_{t+1}^f &= M_t^f \pi_t^m \left(1 - \pi_t^f\right) + W_t^f \left(1 - \pi_t^f\right)\left(1 - p_{m,t}^f\right). &(4)
\end{aligned}$$

To obtain marriage and divorce rates for age groups,[2] we make an assumption that marriage and divorce rates are the same within each age group. That is, if age t and $t+4$ are the youngest and the oldest ages within the same five-year age group, we set

$$p_{m,t}^f = p_{m,t+1}^f = \cdots = p_{m,t+4}^f.$$

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[1] Using stock variables to construct flow variables is common in the marriage literature. For example, Knowles (2013) uses stock variables from the Current Population Survey (CPS) to construct annual marriage and divorce rates.

[2] The age groups are 16–19, 20–24, 25–29, 30–34, 35–39, and 40–44 years old. The first age group covers four years; the remaining groups cover five years each.

Then, from Equation (1), we can derive

$$S^f_{t+5} = S^f_t \left(1 - p^f_{m,t}\right)^5 \left(\prod_{s=0}^{4} \left(1 - \pi^f_{t+s}\right) \right).$$

We are able to solve the above equation for $p^f_{m,t}$ as a function of the stock of the never-married and age-specific mortality rates as

$$p^f_{m,t} = f\left(S^f_t, S^f_{t+5}, \{\pi^f_{t+s}\}^4_{s=0}\right). \tag{5}$$

Once the marriage rate, $p^f_{m,t}$, is determined in the above equation, we can compute divorce rates from Equation (1) through (4). The divorce rate is a function of all the stock variables and age-specific mortality rates as

$$p^f_{d,t} = g\left(S^f_t, S^f_{t+5}, M^f_t, M^f_{t+5}, D^f_t, D^f_{t+5}, W^f_t, W^f_{t+5}, \{\pi^f_{t+s}\}^4_{s=0}\right). \tag{6}$$

Equation (5) and (6) show that we need the number of individuals by age and marital status (stock variables) for every five years, and age-specific mortality rates for each cohort, to calculate marriage and divorce rates by five-year age groups.

For the number of individuals by age and marital status, we do not use the data directly. To obtain the number of individuals by age and marital status that are consistent with the age-specific mortality rates, we first calculate the fraction of females and males in each age and marital status (denoted as s^g_t , m^g_t, d^g_t, w^g_t where $g \in \{f, m\}$) for every five years from the U.S. Census data. Because the U.S. Census data is only available for every 10 years, we compute the equally-weighted average for the midpoint of each decade. Also, we obtain estimates of the mortality rates π^f_t and π^m_t for females and males at each age (see Appendix A.2 for the data sources). After normalizing the total stock of females at age 15 equal to 1 and that of males at age 15 also equal to 1, with a migration term i^m added to the male stock at age 20, we calculate the number of the never-married by

$$S^f_t = s^f_t \left(\prod_{\tau=15}^{t} (1 - \pi^f_\tau) \right), \quad t > 15$$

and likewise for M^f_t, D^f_t, and W^f_t.[3] By doing so, we could compute the number of individuals by age and marital status that are consistent with the age-specific mortality rates. Finally, we use Equation

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[3] We calibrate the migration rate i^m so that the sex ratio of the population aged 20 to 44 in each cohort becomes equal to that of the data.

(5) and (6) to compute marriage and divorce rates for five-year age groups.

Here, we describe the case for the 1950 birth cohort as an example. For the 1950 birth cohort, we use the Census data in 1960, 1970, 1980, 1990, and 2000. From the data, we can compute the fraction of each marital status by gender, $\{s_t^f, m_t^f, d_t^f, w_t^f, s_t^m, m_t^m, d_t^m, w_t^m\}$, for the ages 20, 30, 40, or 50. Furthermore, by taking the equally-weighted average, we are able to compute the fraction of each marital status for the ages, 15, 25, 35, and 45.[4] Once we obtain those fractions, we can compute $\{S_t^f, M_t^f, D_t^f, W_t^f, S_t^m, M_t^m, D_t^m, W_t^m\}$ for five-year age intervals, which allows us to use Equation (5) and (6) to compute marriage and divorce rates for five-year age groups.[5] Thus, marriage and divorce rate for the ages between 16 and 50 can be constructed.

A.2 Data Sources for Demographic Statistics

- *Sex Ratio of the Population Aged 20 to 44:* We calculate the sex ratio of the population aged 20 to 44 from the IPUMS Census data (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010), using the Census conducted approximately 30 years after each cohort's birth year. The Census years used are: 1900 (1870 cohort), 1940 (1910 cohort), 1960 (1930 cohort), 1950 (1950 cohort), and 2000 (1970 cohort). For each Census year, we tabulate unweighted counts of males and females aged 20–44 and compute the ratio of males to females. The resulting sex ratios are reported in Table 1:

Table 1. Sex Ratio of the Population Aged 20–44, by Birth Cohort

Cohort	1870	1910	1930	1950	1970
Census year	1900	1940	1960	1980	2000
Sex ratio	1.056	0.977	0.952	0.942	0.989

- *Life Expectancy at Age 15:* There are two data sources for the life expectancy at age 15. For the years 1880 through 1890, the data is from Haines (1998). For the years 1900 through 2020, we used decennial life tables published by the National Center for Health Statistics; specifically, we use the series of United States Life Tables reports, of which Arias (2012) is the most recent volume we draw from. For each cohort, we assign the value from the life table 50 years after birth (Table 2):

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[4] For example, we calculate the fractions of the people at age 15 by marital status in 1965 by combining the samples at age 15 in 1960 and those in 1970 putting an equal weight to each group.

[5] For the age group 16–19, we use the stocks at age 15 and 20 to compute the marriage and divorce rates assuming that the agents are not able to get married or divorced at age 15.

Table 2. Life Expectancy at Age 15, by Birth Cohort and Sex

Cohort	Life table year	e_{15}^{f} (years)	e_{15}^{m} (years)
1870	1920	49.71	49.05
1910	1960	60.45	54.43
1930	1980	63.83	56.52
1950	2000	65.15	59.90
1970	2020	≈ 66.5	≈ 61.5

The 1970 cohort values are approximate, based on pre-COVID (2019) period life tables; the COVID-19 pandemic temporarily reduced life expectancy but had limited effect on the cohort's marriage-market experience (ages 20–44 correspond to 1990–2014).

- *Age-Specific Mortality Rates:* Age-specific mortality rates are used to calculate the marriage and divorce rates as described above. Those mortality rates are from the National Center for Health Statistics' United States Decennial Life Tables. For the 1910 cohort, mortality rates are interpolated between the 1870 and 1930 cohort values, with 2/3 weight on the 1930 cohort and 1/3 on the 1870 cohort (proportional to the temporal distance). For the 1970 cohort, we use the 1950 cohort's mortality rates as a proxy.

A.3 Data Sources for Marital Statistics

For all five cohorts, we compute 28 marital moments: 12 marriage rates (6 age groups × 2 sexes), 12 divorce rates, 2 median ages at first marriage, and 2 never-married fractions at age 50. Stock fractions of never-married, married, divorced, and widowed individuals at each boundary age (15, 20, 25, 30, 35, 40, 45, 50) are computed as the weighted share of individuals in each marital status using IPUMS person weights and the variable `MARST` (married = codes 1–3, divorced = code 4, widowed = code 5, never-married = code 6). For full-count census years, person weights are set to 1.

- *Marriage and Divorce Rate by Age Group:* Marriage and divorce rates by age group are calculated from the IPUMS Census data (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010) by using the method described above. For each boundary age a, we identify the Census year(s) in which the cohort is observed at that age (year = cohort + a). When the cohort falls between two Census years, we average the stock fractions from the two adjacent censuses. Since the 1890 Census data is missing, we compute the 1870 cohort's age-20 fractions by taking the average of the 1880 and 1900 data.

The 1910 cohort is well covered at all boundary ages from 15 through 50 (1920–1960 Censuses). The 1970 cohort is observed through age 40 (2010 Census); the age-45 stock fraction uses the 2010 Census alone (with an age mismatch of 5 years, interpolated), and the age-50 fraction is unavailable (see the never-married item below).

Table 3 lists the number of samples in the U.S. Census data used to calculate the marriage and divorce rates for the estimation cohorts.

Table 3. The Number of Samples Used for the Calculation of Marriage and Divorce Rate

	1870 Birth Cohort		1930 Birth Cohort		1950 Birth Cohort	
Age	Female	Male	Female	Male	Female	Male
15 years old	54567, 38492*	54969, 39162*	12915, 17288*	13005, 17680*	13645, 39623*	14198, 41259*
20 years old	71149, 40342¶	61185, 37431¶	13498	12862	35054	32381
25 years old	63252, 37729*	62015, 37190*	15162, 11194*	13697, 10626*	28009, 102997*	26541, 101241*
30 years old	35242	38984	11806	11527	94059	91647
35 years old	27185, 7350*	30840, 8202*	12969, 22808*	12256, 21563*	73559, 107343*	71077, 104748*
40 years old	7187	8149	24966	23349	99267	94891
45 years old	5076, 6537*	6007, 7366*	25420, 57261*	23761, 53703*	77202, 109433*	74027, 106694*
50 years old	6225	6920	60922	56503	97207	93223

For the cells marked by *, we calculate the fraction of individuals by marital status by taking an equally-weighted average from two years (thus, the number of the samples in each year is listed). The cells marked by ¶ correspond to the year 1890, for which we do not have data in the Census. Thus, we combine the two years, 1880 and 1900, to compute the fractions.

- *Age at First Marriage:* For the estimation cohorts, we use the median[6] age at first marriage provided by U.S. Census Bureau. They estimate it from the Current Population Survey for the years after 1947. For the years prior to 1947, they estimate it from the decennial censuses.[7] For each cohort, we assign the value which is in the year 30-years-after their birth. That is, we used the age at first marriage in the 1900 data for the 1870 birth cohort. The same assignment rule applies to the 1910 and 1970 cohorts (1940 and 2000 data, respectively).

- *Fraction of the Never-Married by Age 50:* The fraction of the never-married by age 50 is calculated from the IPUMS Census data (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010) for each cohort. For the 1970 cohort, which has not yet reached age 50, we approximate

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[6] We also estimated the 'mean' age at first marriage from the IPUMS Census data, and conducted the benchmark analysis. However, our results did not significantly change.

[7] U.S. Census Bureau, Current Population Survey, March and Annual Social and Economic Supplements.

the never-married fractions at 15% (female) and 20% (male) based on extrapolation from the 2010 observed trends and American Community Survey data.

- *Fraction Married among Individuals Aged 16 to 49:* The fraction of the married aged 16 to 49 is calculated from the IPUMS Census data (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek, 2010). For each cohort, we assign the value which is in the year 30-years-after their birth. That is, we use the fraction married among individuals aged 16 to 49 in the 1900 data for the 1870 birth cohort.

- *Divorce Rate per 1,000 of the Population:* The data for the divorce rate is from Clarke (1995) for the period 1940 to 1990, and Plateris (1973) for the period earlier than 1940. For each cohort, we assign the rate which is in the year 30-years-after their birth. That is, we used the divorce rate in the 1900 data for the 1870 birth cohort.

A.4 Summary of Moments Across All Five Cohorts

Table 4 reports key moments for all five cohorts, showing how the out-of-sample cohorts relate to the estimation sample.

Table 4. Marital Moments: All Five Cohorts

	1870	1910	1930	1950	1970
Female marriage rates					
16–19	0.098	0.108	0.151	0.123	0.047
20–24	0.127	0.142	0.217	0.170	0.110
25–29	0.082	0.094	0.115	0.096	0.100
30–34	0.066	0.086	0.044	0.046	0.054
Female divorce rates					
16–19	0.002	0.011	0.013	0.016	0.038
20–24	0.002	0.006	0.009	0.025	0.034
25–29	0.001	0.004	0.005	0.024	0.025
Summary					
Age 1st mar., F	22.1	21.6	19.9	20.9	24.3
Age 1st mar., M	25.9	24.6	23.1	23.2	26.9
Never mar. F (%)	11.4	7.5	4.6	7.7	≈15
Never mar. M (%)	13.0	7.2	6.0	9.4	≈20
Sex ratio (M/F)	1.056	0.977	0.952	0.942	0.989

The 1910 moments fall between the 1870 and 1930 values for 75% of the moments (21 of 28), with the exceptions concentrated in marriage rates at ages 30–44—consistent with the Depression-era marriage delay that uniquely affected this cohort during its prime marriage years. The 1970 moments display a qualitative break from the estimation-sample cohorts: marriage rates at young ages are dramatically lower (female 16–19: 0.047 vs. 0.098–0.151 for estimation cohorts), divorce rates are substantially higher, and both age at first marriage and never-married fractions are well above any estimation cohort.

B Model Derivations

This appendix derives the beginning-of-period value function for matched or married agents, equation 10 of the main paper, from the underlying decision problem with extreme value shocks.

A matched or married agent of gender g and maturity i in state $s = \{z, i^*, \mu, \mu^*\}$ draws a pair of i.i.d. Gumbel shocks $\boldsymbol{\epsilon}_g = (\epsilon_g^1, \epsilon_g^2)$ that add to the value of being single or married, respectively. Both agents simultaneously decide whether to be married. Marriage requires mutual consent; if either agent prefers to be single, the match dissolves.

The expected value before the realization of shocks is

$$V^{g,i}(s) = \iint \left[\left\{ \Omega^{g,i}(s,2) + \epsilon_g^2 \right\} \mathbf{I}^g \, \mathbf{I}^{g^*} + \left\{ \Omega^{g,i}(s,0) + \epsilon_g^1 \right\} \left(1 - \mathbf{I}^g \, \mathbf{I}^{g^*}\right) \right] dG(\boldsymbol{\epsilon}_g) \, dG(\boldsymbol{\epsilon}_{g^*}), \tag{7}$$

where $\mathbf{I}^g \equiv \mathbf{I}^g(s; \boldsymbol{\epsilon}_g)$ is an indicator for agent g preferring marriage and $\mathbf{I}^{g^*} \equiv \mathbf{I}^{g^*}(s^*(s); \boldsymbol{\epsilon}_{g^*})$ is the corresponding indicator for the partner. Since the shocks are independent across agents, we can factor the double integral. Separating the cases where the partner agrees and disagrees:

$$\begin{aligned} V^{g,i}(s) = {} & \underbrace{\int \max\left\{ \Omega^{g,i}(s,2) + \epsilon_g^2, \ \Omega^{g,i}(s,0) + \epsilon_g^1 \right\} dG(\boldsymbol{\epsilon}_g)}_{\text{agent's optimal choice}} \cdot \underbrace{\int \mathbf{I}^{g^*} \, dG(\boldsymbol{\epsilon}_{g^*})}_{= p^{g^*,i^*}(s^*(s))} \\ & + \underbrace{\int \left\{ \Omega^{g,i}(s,0) + \epsilon_g^1 \right\} dG(\boldsymbol{\epsilon}_g)}_{= \Omega^{g,i}(s,0)} \cdot \left[1 - p^{g^*,i^*}(s^*(s)) \right]. \end{aligned} \tag{8}$$

The first term applies when the partner agrees to marry: the agent chooses optimally between marriage and singlehood. The second term applies when the partner refuses: the agent is single regardless. Applying the log-sum formula for Gumbel shocks to the first term yields equation 10 of the main paper:

$$V^{g,i}(s) = \ln\left[\exp \Omega^{g,i}(s,2) + \exp \Omega^{g,i}(s,0) \right] \, p^{g^*,i^*}(s^*(s)) + \Omega^{g,i}(s,0) \, \left[1 - p^{g^*,i^*}(s^*(s)) \right].$$

C Standard Errors

Our parameters are estimated by minimum distance. Let $m(\theta) \in \mathbb{R}^{n_m}$ denote the vector of model-generated moments evaluated at parameter vector $\theta \in \mathbb{R}^{n_p}$, and let $\hat{m}$ denote the corresponding data moments. The estimator solves

$$\hat{\theta} = \arg\min_{\theta} \left[m(\theta) - \hat{m}\right]' \mathbf{W} \left[m(\theta) - \hat{m}\right],$$

where $\mathbf{W}$ is a diagonal weighting matrix with weights 1 for marriage rates, 100 for divorce rates, 10^{-3} for age at first marriage, and 0.1 for the fraction never married by age 50.

Under standard regularity conditions (see Newey and McFadden (1994), Section 9), the asymptotic distribution of the minimum distance estimator is

$$\sqrt{N}\,(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0,\ V)\,,$$

where

$$V \;=\; \left(G'\mathbf{W}G\right)^{-1} G'\mathbf{W}\,\Sigma\,\mathbf{W}G\,\left(G'\mathbf{W}G\right)^{-1}$$

is the sandwich variance, $G = \partial m(\theta_0)/\partial\theta'$ is the $n_m \times n_p$ Jacobian of the moment function, and $\Sigma = \text{Avar}(\sqrt{N}\,\hat{m})$ is the asymptotic variance-covariance matrix of the data moments.

Computing G. We approximate the Jacobian by forward finite differences:

$$G_{jk} \;\approx\; \frac{m_j(\hat{\theta} + \epsilon_k\, e_k) - m_j(\hat{\theta})}{\epsilon_k},$$

where e_k is the k-th unit vector and $\epsilon_k = 0.01$ for all parameters. This requires $n_p + 1$ equilibrium computations (one per parameter perturbation plus one at the optimum), each involving three cohort-specific equilibria. For the Baseline ($D{+}\omega$, $n_p = 21$) this means 22 solves; for the most parameterized specification (Full, $n_p = 53$) it requires 54.

Computing Σ. The estimation targets—marriage rates, divorce rates, median age at first marriage, and the fraction never married—are nonlinear functions of the marital status fractions (never married, married, divorced, widowed) observed at each age–sex–cohort cell in the Census microdata. We first compute the sampling variance of each fraction under the assumption of independent Bernoulli draws within each cell: for a fraction $\hat{r} = k/n$ observed in a cell of size n, the sampling variance is $\hat{r}(1-\hat{r})/n$.

We also compute the sampling covariance across fractions within each cell. We then propagate this uncertainty to the estimation targets via the delta method. For each (sex, age) cell c, we compute the 28×3 Jacobian J_c of the cohort's 28 targets with respect to the three fractions by numerical differentiation, and accumulate the variance contributions as

$$\Sigma_{jj} = \sum_c \left(J_c \, V_c \, J_c' \right)_{jj},$$

where V_c is the 3×3 sampling covariance matrix of fractions in cell c. This approach correctly handles the median age at first marriage, which is not a proportion and for which the Bernoulli formula does not apply. The resulting Σ is diagonal across cohorts (sampling independence) but accounts for within-cohort covariance through the Jacobian. The sample sizes range from approximately 5,000 to 110,000 per cell (Table 3), yielding sampling standard deviations on the order of 10^{-3} to 10^{-2} for the rates and 10^{-2} for the median age at first marriage.

Interpretation. We compute standard errors using all 84 marital statistics targets (marriage and divorce rates, age at first marriage, fraction never married) across the three cohorts. The 9 demographic targets (sex ratios and life expectancies) are treated as known population quantities. Note that $\mathbf{W}$ is not the efficient weighting matrix Σ^{-1}; consequently the sandwich formula rather than the simpler $(\hat{G}'\Sigma^{-1}\hat{G})^{-1}$ is required.

We compute standard errors for the Baseline ($D+\omega$). The resulting standard errors are reported in parentheses below each parameter estimate in Table 4 of the main paper. Several features are worth noting. The vast majority of parameters are precisely estimated. The aging parameters (Γ), match quality parameters, divorce cost levels, and the age-dependent divorce cost offsets (δ_y, δ_o) all have t-statistics well above 2. In the Baseline, δ_y has $t = 18.3$ and δ_o has $t = 6.9$, leaving no doubt about the statistical significance of age-dependent divorce costs. The three cohort-specific divorce costs are all precisely estimated: ω_{1870} ($t = 22.4$), ω_{1930} ($t = 8.7$), and ω_{1950} ($t = 8.6$). The one exception is the male preference for adolescent partners (α_a^m), which has a large standard error ($t = -1.1$). This is expected: this parameter governs how men value very young women, a margin with little variation in the data because adolescent marriage is rare for men across all cohorts. The female preference for adolescent males (α_a^f) is also only marginally significant ($t = -1.7$). The remaining preference parameters—including the large female preference for old males (α_o^f, $t = 4.6$)—are identified, though the standard errors are larger than in the remaining parameter groups.

Are the divorce cost differences significant? A central finding of this paper is the monotone decline in divorce costs across cohorts. We test whether these differences are statistically significant by computing the standard error of each pairwise difference, accounting for the covariance between estimates. All three differences are highly significant: $\omega_{1870} - \omega_{1930} = 7.89$ ($t = 18.2$), $\omega_{1930} - \omega_{1950} = 3.12$ ($t = 6.5$), and $\omega_{1870} - \omega_{1950} = 11.01$ ($t = 28.1$). The declining trend in divorce costs is not an artifact of sampling uncertainty.

Near-singular directions. The singular value decomposition of the weighted Jacobian $\mathbf{W}^{1/2}G$ reveals that 19 of 21 singular values are well above zero (the largest is 28.7, the 19th is 1.1×10^{-3}), while the last two are near-zero (4.6×10^{-4} and 2.6×10^{-8}). These correspond to α_a^f (female preference for adolescent males) and the $H \to M$ transition parameter Λ_{HM}, which is at a boundary of the parameter space ($\Lambda_{HH} = 1.000$, so $\exp(-19) \approx 0$ and perturbation by $\epsilon = 0.01$ does not move the logistic transform). We use a pseudoinverse of $G'\mathbf{W}G$ (dropping the two near-zero singular values) to handle the resulting near-singularity; the standard errors for the remaining 19 well-identified parameters are unaffected by this choice.

Weighting sensitivity. The Baseline weighting matrix $\mathbf{W}$ upweights divorce rates (weight 100) relative to marriage rates (weight 1), with small weights on age at first marriage (10^{-3}) and the fraction never married (0.1). To check whether the estimates depend on this choice, we re-estimate the Baseline under alternative weights that set all marriage and divorce rate targets to weight 1 and drop the age and never-married targets entirely (weight 0). This removes 12 of 84 targets and equalizes the remaining 72. The parameter estimates are virtually unchanged: the maximum shift across all 21 parameters is 0.11 (in α_a^f, the weakly identified female preference for adolescent males). The divorce cost estimates move by less than 0.01: ω_{1870} remains at 13.18, ω_{1930} at 5.30, and ω_{1950} at 2.18 (vs. 2.17 under baseline weights). The age-dependent offsets are equally stable (δ_y: $2.50 \to 2.48$; δ_o: $0.31 \to 0.31$). The monotone decline in divorce costs and the significance of age-dependent divorce costs are thus robust to the choice of weighting matrix.

D Full Parameter Tables

Tables 5 and 6 report the complete estimated parameter vectors for all nine specifications of the extended model with age-dependent divorce costs. We list raw (optimizer-scale) parameter values and, where applicable, the transformed quantities that enter the model directly: aging transition probabilities Γ, the match-quality matrix Λ, and the type threshold θ. The parameter groups are **C** (preferences $\alpha_a^{f,m}, \alpha_y^{f,m}, \alpha_o^{f,m}$); **D** (aging transitions $\Gamma_f(1,2), \Gamma_m(1,2), \Gamma_f(2,3), \Gamma_m(2,3)$); **F** (marriage friction ϕ); **E** (match quality θ and four λ raw parameters); **B** (divorce cost ω, common or cohort-specific); **G** (age-dependent divorce cost shifters δ_y, δ_o).

D.1 Baseline (D+ω): Standard Errors

Table 5 reports the baseline parameter estimates with the sandwich standard errors used in the main paper (see Appendix C). The standard error of the raw λ_1 parameter is reported as "—": λ_1 governs the $H \rightarrow M$ transition probability Λ_{HM}, which is at the boundary ($\Lambda_{HH} = 1.000$, raw $\lambda_1 = -18.97$ at the lower edge of the feasible region). The Jacobian column for λ_1 is numerically zero under the $\epsilon = 0.01$ perturbation, so its SE is not identified. All remaining 20 parameters are precisely estimated; in particular α_a^m and α_a^f have the largest SEs because the data contain little variation in adolescent-age marriage.

D.2 All Nine Specifications: Raw Parameter Estimates

Table 6 consolidates the raw estimates for every specification on a single landscape page. When a parameter group varies by cohort, the entry shows the three cohort values as $\{1870 \ / \ 1930 \ / \ 1950\}$.

Table 5. Baseline ($D+\omega$): Parameter Estimates with Sandwich Standard Errors

#	Parameter	Estimate	Std. Error	Group
1	α_a^f	-43.674	25.351	C
2	α_a^m	-5.767	5.269	C
3	α_y^f	-2.010	1.624	C
4	α_y^m	1.354	0.055	C
5	α_o^f	26.799	5.875	C
6	α_o^m	-0.541	0.043	C
7	cgf_1 (raw)	0.393	0.062	D
8	cgm_1 (raw)	0.775	0.076	D
9	cgf_2 (raw)	1.996	0.060	D
10	cgm_2 (raw)	1.869	0.110	D
11	ϕ	10.344	0.043	F
12	θ	0.497	0.021	E
13	λ_1 (raw)	-18.969	—	E
14	λ_2 (raw)	4.324	0.039	E
15	λ_3 (raw)	5.926	0.076	E
16	λ_4 (raw)	-4.887	0.741	E
17	ω_{1870}	13.182	0.588	B
18	ω_{1930}	5.296	0.610	B
19	ω_{1950}	2.175	0.252	B
20	δ_y	2.503	0.137	G
21	δ_o	0.306	0.044	G
Transformed (probability-scale) statistics				
	$\Gamma_f(1,2)$	0.597		D
	$\Gamma_f(2,3)$	0.880		D
	$\Gamma_m(1,2)$	0.685		D
	$\Gamma_m(2,3)$	0.866		D
	$\Lambda(1,1)$	1.000		E
	$\Lambda(1,2)$	0.000		E
	$\Lambda(2,1)$	0.167		E
	$\Lambda(2,2)$	0.002		E
	$\Lambda(2,3)$	0.830		E
	$\Lambda(3,2)$	≈ 0		E
	WSSE	0.056		

Notes: Sandwich standard errors with 84 marital-statistics targets, finite-difference Jacobian ($\epsilon = 0.01$), and a delta-method-based data variance–covariance matrix; see Section C. "—" for λ_1 indicates the raw parameter is at a boundary so its Jacobian column is numerically zero. Probability-scale statistics (Γ, Λ) are deterministic transforms of the raw parameters.

Table 6. Parameter Estimates for All Nine Specifications (raw / optimizer-scale)

Parameter	Pooled	*D*	*D*+ω	*D*+ω+α	*D*+ω+Γ	*D*+ω+λ	*D*+ω+ϕ	*D*+ω+α+Γ	Full
# Params	19	19	21	33	29	31	23	41	53
(C) Preferences									
α_a^f	−840.3	−56.4	−43.7	$\{-157.2/-46.4/-40.0\}$	−13.7	−6.6	−125.7	$\{-979.5/-62.4/-148.2\}$	$\{-3.4/-7.6/-25.2\}$
α_a^m	−438.1	−5.4	−5.8	$\{-4.5/-4.0/-6.0\}$	−38.8	−230.0	−978.1	$\{-4.9/-4.0/-10.8\}$	$\{-221.4/27.1/-457.8\}$
α_y^f	24.2	−42.0	−2.0	$\{-16.0/9.3/-0.8\}$	−0.6	−0.9	9.4	$\{-22.6/15.1/0.2\}$	$\{-1.3/-0.4/0.1\}$
α_y^m	1.0	0.2	1.4	$\{1.0/2.7/1.0\}$	17.5	−34.0	−1.2	$\{1.2/2.9/0.6\}$	$\{-12.0/-2.1/-48.0\}$
α_o^f	594.8	363.0	26.8	$\{113.3/67.0/12.0\}$	−3.2	−2.1	73.7	$\{280.5/48.4/39.3\}$	$\{-2.5/-2.2/-2.3\}$
α_o^m	−0.8	−1.4	−0.5	$\{-0.7/-0.4/-0.8\}$	2.4	147.7	−2.2	$\{-0.6/-0.5/-0.8\}$	$\{189.1/190.0/141.1\}$
(D) Aging (raw)									
cgf_1	−0.69	−0.91	0.39	0.81	$\{0.50/0.26/0.46\}$	−1.50	−1.17	$\{1.00/0.77/0.49\}$	$\{-2.62/-0.38/-1.17\}$
cgm_1	0.63	0.47	0.78	0.89	$\{1.50/0.83/0.54\}$	0.15	0.18	$\{1.29/0.62/0.57\}$	$\{0.98/0.51/0.19\}$
cgf_2	2.92	3.14	2.00	1.86	$\{2.32/2.39/2.54\}$	3.19	3.07	$\{1.47/1.64/2.12\}$	$\{3.50/2.94/2.99\}$
cgm_2	3.14	3.32	1.87	1.97	$\{2.50/1.78/2.45\}$	3.61	3.48	$\{2.15/2.24/2.16\}$	$\{3.74/2.99/2.86\}$
(F) Marriage cost									
ϕ	19.69	18.23	10.34	9.21	7.50	21.01	$\{16.4/8.4/13.0\}$	8.45	$\{24.96/18.54/16.98\}$
(E) Match quality									
θ	1.00	0.30	0.50	0.52	4.16	$\{1.94/3.91/3.89\}$	2.29	0.55	$\{0.97/3.36/3.64\}$
λ_1	−61.7	−16.2	−19.0	−35.2	−16.9	$\{-96.1/-134.0/-15.2\}$	−175.4	−12.8	$\{-373.8/-204.1/-13.2\}$
λ_2	4.79	5.47	4.32	6.34	2.27	$\{3.31/1.25/-0.85\}$	5.40	5.10	$\{3.63/1.43/-0.84\}$
λ_3	6.37	6.28	5.93	7.73	2.99	$\{6.88/3.85/0.10\}$	6.49	6.47	$\{7.20/3.72/0.23\}$
λ_4	−2.47	−3.54	−4.89	−7.68	0.47	$\{-111.7/-93.9/-1.65\}$	−2.86	−13.46	$\{-79.0/-98.4/-1.64\}$
(B) Divorce cost									
ω_{1870}	—	—	13.18	15.03	9.89	31.74	23.61	15.68	43.07
ω_{1930}	—	—	5.30	11.55	5.40	0.02	31.25	12.77	0.00
ω_{1950}	—	—	2.17	2.70	2.30	15.62	13.03	2.82	11.36
ω (common)	8.23	7.19	—	—	—	—	—	—	—
(G) Age-dependent divorce cost shifters									
δ_y	2.71	3.19	2.50	2.52	3.50	2.55	2.05	2.10	4.25
δ_o	0.25	1.34	0.31	0.51	−0.71	−1.47	0.65	0.46	−1.00
WSSE	0.201	0.067	0.056	0.052	0.050	0.048	0.053	0.046	0.041

Notes: Each column reports the estimated parameter vector for one specification. When a parameter group varies by cohort in a given specification, the entry is shown as {1870 / 1930 / 1950}. "—" marks parameters that do not exist in that specification. WSSE is the weighted sum of squared errors at the optimum across the 84 marital-statistics targets and the 9 demographic targets (3 cohorts × marriage rates, divorce rates, age at first marriage, and fraction never-married).

D.3 Match-Quality Transition Probabilities Across Specifications

Table 7 extracts the implied match-quality transition probabilities $\Lambda(i,j)$ at each estimate for ease of comparison.

Table 7. Implied Λ Transition Probabilities Across Specifications

$\Lambda(i,j)$	Pooled	D	$D+\omega$	$D+\omega+\alpha$	$D+\omega+\Gamma$	$D+\omega+\lambda$	$D+\omega+\phi$	$D+\omega+\alpha+\Gamma$	Full
$\Lambda(1,1)$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\Lambda(2,1)$	0.171	0.308	0.167	0.200	0.317	0.169	0.251	0.202	0.160
$\Lambda(2,2)$	0.001	0.001	0.002	0.000	0.033	0.394	0.001	0.001	0.372
$\Lambda(2,3)$	0.828	0.691	0.830	0.800	0.650	0.437	0.748	0.797	0.468
$\Lambda(3,3)$	0.922	0.972	0.993	1.000	0.385	0.839	0.946	1.000	0.838

Notes: For specifications where Λ is cohort-specific ($D+\omega+\lambda$ and Full), the entry shows the 1950 cohort value; the 1870 and 1930 values can be reconstructed from the raw λ estimates in Table 6. $\Lambda(1,2) = 1 - \Lambda(1,1)$ is governed by raw λ_1 via $\Lambda_{HM} = \text{logistic}(\lambda_1)$, and $\Lambda(3,2) = 1 - \Lambda(3,3)$ by raw λ_4 via $\Lambda_{LM} = \text{logistic}(\lambda_4)$. In every specification λ_1 sits near -19 or below, driving $\Lambda(1,1) \approx 1.000$; λ_4 varies, so $\Lambda(3,3)$ varies correspondingly across specifications (see $\Lambda(3,3)$ row above; the Baseline value is 0.993).

D.4 Summary: WSSE Across Specifications

Table 8. Summary: WSSE Across Specifications (Age-Dependent Divorce Costs)

Spec	# Params	WSSE	What varies by cohort
Pooled	19	0.201	Nothing (common ω)
D	19	0.067	Demographics only (common ω)
$D+\omega$ (Baseline)	21	0.056	ω
$D+\omega+\alpha$	33	0.052	C, ω
$D+\omega+\Gamma$	29	0.050	D, ω
$D+\omega+\lambda$	31	0.048	E, ω
$D+\omega+\phi$	23	0.053	F, ω
$D+\omega+\alpha+\Gamma$	41	0.046	C, D, ω
Full	53	0.041	C, D, F, E, ω

E Model Fit Details

Table 9 reports the complete model fit for the baseline specification $D+\omega$ (Baseline). For each of the 93 targeted moments we show the data value, the model prediction, and the weighted squared error. The weighting scheme assigns weight 1 to marriage-rate moments, weight 100 to divorce-rate moments, weight 10^{-3} to median age at first marriage, and weight 0.1 to the never-married-by-50 fractions. The overall WSSE is 0.056.

Table 9. Baseline $D+\omega$ (Baseline): Complete Model Fit (93 Targets)

Target	Data	Model	Wgt.Sq.Err	Target	Data	Model	Wgt.Sq.Err
Marriage rates — 1870 cohort (weight = 1)							
mar_f_1619	0.0979	0.1143	0.000271	mar_m_1619	0.0205	0.0544	0.001147
mar_f_2024	0.1267	0.1709	0.001948	mar_m_2024	0.1023	0.1001	0.000005
mar_f_2529	0.0824	0.0817	0.000000	mar_m_2529	0.0865	0.0806	0.000034
mar_f_3034	0.0656	0.0460	0.000382	mar_m_3034	0.0702	0.0624	0.000061
mar_f_3539	0.0284	0.0399	0.000132	mar_m_3539	0.0427	0.0546	0.000143
mar_f_4044	0.0246	0.0389	0.000203	mar_m_4044	0.0488	0.0520	0.000011
Divorce rates — 1870 cohort (weight = 100)							
div_f_1619	0.0025	0.0013	0.000143	div_m_1619	0.0025	0.0017	0.000051
div_f_2024	0.0019	0.0015	0.000021	div_m_2024	0.0018	0.0018	0.000000
div_f_2529	0.0013	0.0017	0.000010	div_m_2529	0.0006	0.0018	0.000154
div_f_3034	0.0015	0.0018	0.000011	div_m_3034	0.0011	0.0018	0.000050
div_f_3539	0.0004	0.0019	0.000227	div_m_3539	0.0007	0.0019	0.000138
div_f_4044	0.0003	0.0019	0.000272	div_m_4044	0.0012	0.0019	0.000039
Age at first marriage and never-married — 1870 cohort							
age_f (wt 10^{-3})	22.10	22.81	0.000510	age_m (wt 10^{-3})	25.90	26.22	0.000103
nev_mar_f (wt 0.1)	0.1136	0.0721	0.000172	nev_mar_m (wt 0.1)	0.1302	0.1053	0.000062
Marriage rates — 1930 cohort (weight = 1)							
mar_f_1619	0.1512	0.1435	0.000060	mar_m_1619	0.0482	0.0882	0.001601
mar_f_2024	0.2169	0.2016	0.000233	mar_m_2024	0.1812	0.1444	0.001348

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Target	Data	Model	Wgt.Sq.Err	Target	Data	Model	Wgt.Sq.Err
mar_f_2529	0.1150	0.0769	0.001449	mar_m_2529	0.1372	0.0979	0.001542
mar_f_3034	0.0445	0.0379	0.000043	mar_m_3034	0.0801	0.0660	0.000198
mar_f_3539	0.0212	0.0291	0.000063	mar_m_3539	0.0319	0.0556	0.000566
mar_f_4044	0.0216	0.0257	0.000017	mar_m_4044	0.0422	0.0526	0.000108
Divorce rates — 1930 cohort (weight = 100)							
div_f_1619	0.0129	0.0105	0.000567	div_m_1619	0.0116	0.0106	0.000105
div_f_2024	0.0089	0.0090	0.000003	div_m_2024	0.0092	0.0071	0.000469
div_f_2529	0.0047	0.0072	0.000635	div_m_2529	0.0044	0.0061	0.000290
div_f_3034	0.0055	0.0059	0.000021	div_m_3034	0.0042	0.0056	0.000192
div_f_3539	0.0038	0.0052	0.000202	div_m_3539	0.0031	0.0053	0.000506
div_f_4044	0.0081	0.0049	0.001061	div_m_4044	0.0072	0.0052	0.000381
Age at first marriage and never-married — 1930 cohort							
age_f (wt 10^{-3})	19.90	21.57	0.002789	age_m (wt 10^{-3})	23.10	24.17	0.001141
nev_mar_f (wt 0.1)	0.0456	0.0805	0.000122	nev_mar_m (wt 0.1)	0.0602	0.0653	0.000003
Marriage rates — 1950 cohort (weight = 1)							
mar_f_1619	0.1232	0.1358	0.000159	mar_m_1619	0.0587	0.0903	0.000996
mar_f_2024	0.1703	0.1954	0.000630	mar_m_2024	0.1488	0.1532	0.000020
mar_f_2529	0.0957	0.0887	0.000048	mar_m_2529	0.1117	0.1049	0.000047
mar_f_3034	0.0464	0.0495	0.000009	mar_m_3034	0.0558	0.0713	0.000238
mar_f_3539	0.0322	0.0372	0.000025	mar_m_3539	0.0392	0.0587	0.000379
mar_f_4044	0.0161	0.0318	0.000246	mar_m_4044	0.0247	0.0538	0.000848
Divorce rates — 1950 cohort (weight = 100)							

Continued on next page

Target	Data	Model	Wgt.Sq.Err	Target	Data	Model	Wgt.Sq.Err
div_f_1619	0.0164	0.0240	0.005785	div_m_1619	0.0183	0.0229	0.002082
div_f_2024	0.0254	0.0207	0.002147	div_m_2024	0.0230	0.0198	0.001026
div_f_2529	0.0239	0.0166	0.005417	div_m_2529	0.0233	0.0162	0.005038
div_f_3034	0.0108	0.0137	0.000827	div_m_3034	0.0101	0.0137	0.001326
div_f_3539	0.0157	0.0120	0.001360	div_m_3539	0.0133	0.0123	0.000097
div_f_4044	0.0068	0.0111	0.001906	div_m_4044	0.0066	0.0116	0.002465
Age at first marriage and never-married — 1950 cohort							
age_f (wt 10^{-3})	20.90	21.89	0.000973	age_m (wt 10^{-3})	23.20	23.83	0.000400
nev_mar_f (wt 0.1)	0.0766	0.0786	0.000000	nev_mar_m (wt 0.1)	0.0936	0.0620	0.000099

Table 10 reports the non-targeted "other" moments from the baseline $D{+}\omega$ (Baseline) equilibrium: the stock of married individuals (as a fraction of the population aged 16–49) and the divorce rate per 1000 population.

Table 10. Baseline $D{+}\omega$ (Baseline): Non-Targeted Moments

Cohort	Moment	Data	Model
1870	Fraction married, female	0.597	0.306
1870	Fraction married, male	0.484	0.275
1870	Divorce rate per 1000	0.700	1.853
1930	Fraction married, female	0.726	0.299
1930	Fraction married, male	0.639	0.272
1930	Divorce rate per 1000	2.200	5.442
1950	Fraction married, female	0.625	0.299
1950	Fraction married, male	0.566	0.271
1950	Divorce rate per 1000	5.200	12.543

[†] These moments are computed from the model equilibrium but are not included in the objective function. The model correctly predicts the *direction* of changes across cohorts (falling marriage stocks, rising divorce rates) but over-predicts the divorce rate level and under-predicts the married stock.

F Sensitivity to Weighting

The benchmark estimation uses diagonal weights that reflect the relative importance we assign to different moment groups: marriage-rate moments receive weight 1, divorce-rate moments receive weight 100, median age at first marriage receives weight 10^{-3}, and the never-married-by-50 fractions receive weight 0.1. This appendix investigates sensitivity to this choice by re-estimating the Baseline specification $D{+}\omega$ (Baseline) under an alternative weighting scheme that drops the age and never-married targets entirely (weight 0) and equalizes the remaining 72 marriage and divorce rate targets at weight 1.

Table 11. Sensitivity to Weighting: $D{+}\omega$ (Baseline) Parameter Estimates

Parameter	Benchmark	Rates Only
α_a^f	-43.67	-43.78
α_a^m	-5.77	-5.76
α_y^f	-2.01	-2.00
α_y^m	1.35	1.35
α_o^f	26.80	26.80
α_o^m	-0.54	-0.54
ϕ	10.34	10.34
θ	0.497	0.497
ω_{1870}	13.18	13.18
ω_{1930}	5.30	5.30
ω_{1950}	2.17	2.18
δ_y	2.50	2.48
δ_o	0.31	0.31

Notes: Rates-only weights set all marriage and divorce rate targets to weight 1 and drop age at first marriage and never-married targets (weight 0). The maximum parameter shift is 0.11 (in α_a^f). All divorce cost estimates and age-dependent offsets are stable to two decimal places.

G Base Model Results (Without Age-Dependent Divorce Costs)

For comparison with the extended model, this appendix reports estimation results from the base model specifications (Pooled through Full), which do not include age-dependent divorce costs (i.e., $\delta_y = \delta_o = 0$ is imposed). The base model is otherwise identical to the extended model: the same target moments, weighting matrix, and optimizer settings are used.

Table 12 summarizes the WSSE values. The key finding is that allowing age-dependent divorce costs (the +G extension) consistently improves fit. The improvement is largest for the baseline specification: the base $D+\omega$ (without age-dep) achieves WSSE = 0.087 compared with $D+\omega$ (Baseline, with age-dep) = 0.056, a 36% reduction. Even the most flexible base specification (Full, WSSE = 0.056) is comparable to the much more parsimonious $D+\omega$ (Baseline).

Table 12. WSSE: Base Model (No Age-Dependent Divorce Costs) vs. Extended Model

Spec	# Params (base)	WSSE (base)	# Params (+G)	WSSE (+G)
Pooled	17	—	19	0.201
D	17	—	19	0.067
$D+\omega$	19	0.087	21	0.056
$D+\omega+\alpha$	31	0.059	33	0.052
$D+\omega+\Gamma$	27	0.063	29	0.050
$D+\omega+\lambda$	29	0.059	31	0.048
$D+\omega+\phi$	21	0.062	23	0.053
$D+\omega+\alpha+\Gamma$	39	0.058	41	0.046
Full	51	0.056	53	0.041

[†] Base Pooled and D WSSE values not reported as those specifications do not allow cohort-specific divorce costs and thus are not directly comparable.
Full parameter tables for the base model: Available upon request.

H Computational Details

H.1 Optimization Algorithm

The model is estimated by minimizing the weighted sum of squared errors (WSSE) between data moments and model-implied moments. Because the objective function does not have an analytical gradient—each evaluation requires solving for a steady-state equilibrium via fixed-point iteration—we use derivative-free optimization methods.

The primary optimizer is BOBYQA (Powell, 2009), a trust-region method for bound-constrained derivative-free optimization. BOBYQA constructs a quadratic interpolation model of the objective function within a trust region, updating the model as new function evaluations are obtained. We set the initial trust-region radius $\rho_{\text{beg}} = 1.0$ and the final trust-region radius $\rho_{\text{end}} = 10^{-8}$.

After BOBYQA converges, we polish the solution using the Nelder-Mead simplex algorithm with parameters $\alpha = 1$ (reflection), $\gamma = 2$ (expansion), $\rho = 0.5$ (contraction), and $\sigma = 0.5$ (shrinkage). The Nelder-Mead phase runs for up to 50,000 iterations with a tolerance of 10^{-10}.

H.2 Multi-Start Strategy

For specifications with more than 20 parameters ($D+\omega+\alpha$ through Full), the non-convexity of the objective function is a serious concern. We employ a multi-start strategy:

1. Generate 200–400 starting points using Sobol quasi-random sequences over the feasible parameter space.
2. Evaluate the objective function at each starting point and rank them by WSSE.
3. Select the top 8 starting points and refine each with a full BOBYQA run.
4. Polish the best solution with Nelder-Mead.

H.3 Equilibrium Computation

Each function evaluation requires solving three steady-state equilibria (one per cohort: 1870, 1930, 1950). Each equilibrium is computed via fixed-point iteration on the allocation of individuals across marital states and match qualities, with a convergence tolerance of 10^{-9} and a maximum of 5,000 iterations. Typical convergence requires 300–3,500 iterations (see the iteration counts in the output files).

H.4 Implementation

The estimation code is written in Fortran 90 and compiled with `gfortran` using the `-O3` optimization flag. Total function evaluations per specification typically range from 5,000 to 20,000, depending on the number of parameters and the difficulty of the optimization landscape.

I Equilibrium Properties

Table 13 reports the stock of married individuals (as a fraction of the population aged 16–49) and the crude divorce rate (per 1000 population) for each cohort and sex, comparing the data with the model predictions from specification $D{+}\omega$ (Baseline).

Table 13. Equilibrium Properties: Married Stock and Divorce Rate

		Data	Model ($D{+}\omega$ (Baseline))
Fraction of population aged 16–49 that is married			
1870	Female	0.597	0.306
1870	Male	0.484	0.275
1930	Female	0.726	0.299
1930	Male	0.639	0.272
1950	Female	0.625	0.299
1950	Male	0.566	0.271
Divorce rate per 1000 population			
1870		0.700	1.853
1930		2.200	5.442
1950		5.200	12.543

† Data sources are described in Section A of this Online Appendix. The model under-predicts the married stock by roughly half, reflecting the stylized nature of the three-type framework. The model correctly captures the qualitative pattern: the married stock peaks for the 1930 cohort (the "marriage boom" generation) and the divorce rate rises monotonically across cohorts. The model over-predicts the level of the crude divorce rate, in part because the model's age structure (six five-year age groups from 16–44) does not include older married couples who contribute to the denominator of the crude rate.

J Counterfactual Exercises

This appendix describes three counterfactual exercises that decompose the sources of changing marriage and divorce patterns across cohorts. All counterfactuals use the baseline $D{+}\omega$ (Baseline) parameter estimates.

J.1 Demographics Swap

We assign the 1950 cohort the demographic environment of the 1870 cohort—specifically, the sex ratio and age-specific mortality rates—while retaining the 1950 cohort's estimated divorce cost ω_{1950} and all other preference parameters. Comparing the counterfactual equilibrium with the actual 1950 equilibrium isolates the contribution of demographic change to the observed shifts in marriage and divorce rates.

Swapping in the 1870 demographic environment raises female marriage rates at most ages (e.g., the 20–24 rate rises from 0.195 to 0.204) while substantially lowering female divorce rates at younger ages (the 16–19 rate falls from 0.024 to 0.011), indicating that the more favorable sex ratio of the earlier cohort encouraged marriage and discouraged divorce. Male age at first marriage rises by 1.5 years, reflecting the tighter marriage market for men under the 1870 sex ratio.

Table 14. Counterfactual 1: Demographics Swap

	1950 Cohort			
Moment	Baseline	CF (1870 Demog.)	1950 Data	1870 Data
Female marriage rates				
16–19	0.1358	0.1400	0.1232	0.0979
20–24	0.1954	0.2038	0.1703	0.1267
25–29	0.0887	0.0877	0.0957	0.0824
30–34	0.0495	0.0521	0.0464	0.0656
35–39	0.0372	0.0452	0.0322	0.0284
40–44	0.0318	0.0430	0.0161	0.0246
Female divorce rates				
16–19	0.0240	0.0109	0.0164	0.0025
20–24	0.0207	0.0125	0.0254	0.0019
25–29	0.0166	0.0145	0.0239	0.0013
30–34	0.0137	0.0159	0.0108	0.0015
35–39	0.0120	0.0168	0.0157	0.0004
40–44	0.0112	0.0172	0.0068	0.0003
Summary moments				
Age first marriage, female	21.886	21.966	20.900	22.100
Age first marriage, male	23.833	25.339	23.200	25.900
Never-married by 50, female	0.0786	0.0485	0.0766	0.1136
Never-married by 50, male	0.0620	0.0879	0.0936	0.1302

Notes: "Baseline" is the model evaluated at 1950 estimated parameters and demographics. "CF" replaces the 1950 demographic environment (sex ratio, mortality) with the 1870 environment.

J.2 Divorce Cost Equalization

We assign all three cohorts the 1870 divorce cost $\omega_{1870} = 13.18$, while retaining their own demographic environments. This isolates the role of falling divorce costs (from $\omega_{1870} = 13.18$ to $\omega_{1930} = 5.30$ to $\omega_{1950} = 2.17$) in explaining the rise in divorce rates and changes in marriage patterns.

Imposing the high 1870 divorce cost on later cohorts dramatically reduces divorce rates: the aggregate divorce rate falls from 12.54 to 2.71 per thousand for the 1950 cohort and from 5.44 to 2.66 for the 1930 cohort, confirming that declining divorce costs are the dominant force behind rising divorce. Marriage rates also decline modestly, consistent with the option-value channel in which easier divorce encourages entry into marriage.

Table 15. Counterfactual 2: Divorce Cost Equalization

	1930 Cohort			1950 Cohort		
Moment	Data	Baseline	ω_{1870}	Data	Baseline	ω_{1870}
Female marriage rates						
20–24	0.2169	0.2016	0.1932	0.1703	0.1954	0.1995
25–29	0.1150	0.0769	0.0688	0.0957	0.0887	0.0699
Female divorce rates						
16–19	0.0129	0.0105	0.0052	0.0164	0.0240	0.0049
20–24	0.0089	0.0090	0.0045	0.0254	0.0207	0.0043
25–29	0.0047	0.0072	0.0036	0.0239	0.0166	0.0035
30–34	0.0055	0.0059	0.0029	0.0108	0.0137	0.0029
35–39	0.0038	0.0052	0.0026	0.0157	0.0120	0.0026
40–44	0.0081	0.0049	0.0024	0.0068	0.0112	0.0025
Summary moments						
Agg. divorce rate (/1000)	2.200	5.442	2.659	5.200	12.544	2.712
Never-married, female	0.0456	0.0805	0.0912	0.0766	0.0786	0.0836
Never-married, male	0.0602	0.0653	0.0778	0.0936	0.0620	0.0748

Notes: "Baseline" uses each cohort's own estimated ω; "ω_{1870}" replaces it with the 1870 divorce cost while retaining the cohort's own demographics. The 1870 cohort is unaffected by construction.

J.3 Removing Age-Dependence in Divorce Costs

We set $\delta_y = \delta_o = 0$ (no age-dependent divorce cost shifters) while retaining the estimated level of ω for each cohort. This counterfactual reveals how age-dependent divorce costs shape the *age profile* of divorce—the hump-shaped pattern where divorce rates peak at younger ages and decline with age.

Without age-dependence, the declining age profile of divorce vanishes entirely: for the 1950 cohort, the female divorce rate at ages 40–44 rises from 0.011 to 0.074, while the rate at ages 16–19 falls from 0.024 to 0.016. The effect is even more dramatic on marriage, as never-married rates by age 50 explode (e.g., from 0.062 to 0.706 for males in the 1950 cohort), confirming that age-dependent divorce costs are essential for generating realistic marriage and divorce age profiles.

Table 16. Counterfactual 3: Removing Age-Dependence ($\delta_y = \delta_o = 0$)

	1870		1930		1950	
Age group	With δ	Without	With δ	Without	With δ	Without
Female divorce rates						
16–19	0.0013	0.0008	0.0105	0.0037	0.0240	0.0161
20–24	0.0015	0.0017	0.0090	0.0060	0.0207	0.0297
25–29	0.0017	0.0027	0.0072	0.0088	0.0166	0.0453
30–34	0.0018	0.0036	0.0059	0.0112	0.0137	0.0580
35–39	0.0019	0.0042	0.0052	0.0129	0.0120	0.0673
40–44	0.0019	0.0047	0.0049	0.0141	0.0112	0.0740
Male divorce rates						
16–19	0.0017	0.0052	0.0106	0.0291	0.0229	0.0613
20–24	0.0018	0.0048	0.0071	0.0213	0.0198	0.0571
25–29	0.0018	0.0044	0.0061	0.0163	0.0162	0.0541
30–34	0.0018	0.0042	0.0056	0.0138	0.0137	0.0525
35–39	0.0019	0.0041	0.0053	0.0128	0.0123	0.0518
40–44	0.0019	0.0040	0.0052	0.0123	0.0116	0.0515
Never-married by 50						
Female	0.0721	0.7409	0.0805	0.6120	0.0786	0.4022
Male	0.1053	0.8545	0.0653	0.7955	0.0620	0.7063

Notes: "With δ" is the baseline model with estimated age-dependent divorce cost shifters δ_y and δ_o; "Without" sets both to zero. Each cohort retains its own estimated ω.

K Age at First Marriage and Never-Married Fit

Table 17 provides a focused comparison of the model's fit to median age at first marriage and the fraction never-married by age 50, which are the moments most directly related to the extensive margin of marriage. The age at first marriage moments receive a low weight (10^{-3}) in the objective function because they are measured in years rather than rates, while the never-married fractions receive a weight of 0.1.

Table 17. Age at First Marriage and Never-Married by 50: Data vs. Model ($D+\omega$ (Baseline))

Cohort	Moment	Data	Model	Wgt. Sq. Err
Median age at first marriage (weight $= 10^{-3}$)				
1870	Female	22.10	22.81	0.000510
1870	Male	25.90	26.22	0.000103
1930	Female	19.90	21.57	0.002789
1930	Male	23.10	24.17	0.001141
1950	Female	20.90	21.89	0.000973
1950	Male	23.20	23.83	0.000400
Fraction never-married by age 50 (weight $= 0.1$)				
1870	Female	0.1136	0.0721	0.000172
1870	Male	0.1302	0.1053	0.000062
1930	Female	0.0456	0.0805	0.000122
1930	Male	0.0602	0.0653	0.000003
1950	Female	0.0766	0.0786	0.000000
1950	Male	0.0936	0.0620	0.000099

[†] The model over-predicts the age at first marriage by 0.6–1.7 years across cohorts, with the largest discrepancy for the 1930 cohort (females: 21.6 vs. 19.9 in the data). This reflects the tension between fitting the marriage boom's high marriage rates and its low age at first marriage. For the never-married fractions, the model fits the 1950 cohort well (females: 7.9% model vs. 7.7% data) but over-predicts the 1930 female never-married fraction (8.1% vs. 4.6%) and under-predicts the 1870 female fraction (7.2% vs. 11.4%). The total weighted squared error contribution from these 12 moments is 0.006, representing about 11% of the total WSSE of 0.056.

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