An Empirical Study of Darwin's Theory of Mate Choice

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Abstract

In Darwin's (1871) theory of mate choice, males compete, females choose, males are more differentiated, and highly ornamented males mate earlier. This paper reexamines the latter three hypotheses of Darwin about human mate selection by estimating a Nash marriage market equilibrium model using all restrictions implied by marriage theory. The MLE method employed involves solving for steady state marriage sets. An index of marriageability is proposed to allow for incorporation of data on education, wages, and unobserved heterogeneity in a computationally manageable way. Results do not support Darwin's claim: males are as choosy as females. However, the notion that males are more differentiated than females and that marriageable (highly ornamented) males tend to marry earlier are both supported by my results. Education is more important than wage as a marriageable trait for both men and women. Females in cities tend to have more desirable unobserved characteristics when compared with males in cities and females in suburbs. The marriage market appears to be sensitive to changes in agents' levels of education and variability in wages.

Keywords: Assortative Mating, Inequality, Marriage Hazard, Structural Estimation, Unobserved Heterogeneity, Classification Errors

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1 Introduction

Peacocks' tails seem to have no survival value, and therefore appear not to play a role in natural selection. To account for the existence of such apparently useless characteristics, Darwin (1871) proposed another reason for evolutionary change: sexual selection through mate choice. The concept of sexual selection is a way of describing how differences in reproductive success lead to evolutionary change: any traits that help in competing for sexual mates will tend to spread through the species. Darwin envisioned two main processes of sexual selection: male competition and female choice. Males compete to inseminate females by beating up other males, competing for the resources necessary to mate, or courting a female. Females exercise sexual choice, picking more attractive males over the plainer. These two processes imply that males are more differentiated than females and better males mate earlier. R. A. Fisher (1915, 1930) formalized Darwin's theory of mate choice and proposed that female preferences would catch up with male ornamentation in a self-reinforcing cycle, producing a positive-feedback loop in evolution.[1] Darwin's theory of mate choice has met with hostility in the century since its promulgation. But not until the past two decades has there been a renaissance of scientific interest in sexual selection theory, along with increasing numbers of experiments on how animals choose their mates.[2]

The concept of mate selection has also sown seeds in economics. Becker (1973) first formalized the theory of assortative mating. Recent theoretical models on assortative matching (Shimer and Smith (2000), Burdett and Coles (1997), and Sattinger (1995)) depart from neoclassical assignment literature in assuming that match creation is time consuming. Because matching precludes further searches, agents must weigh the opportunity costs of searching for better partners against the benefits of immediate match production. Except for a few studies such as Pencavel (1998), little is known about the empirical content of assortative mating, in particular, sexual variation in mating.

Numerous studies have also focused on the relation between sorting and intergenerational transmission of inequality.[3] These models are not concerned with sexual selection, which constitutes the main aspect of Darwin's theory. Instead of establishing a relationship between (genetic) transmission of traits and inequality, this paper steps back and seeks an answer to the fundamental question of whether human sexual selection behavior has in fact occurred as described by Darwin. If sexual difference

[1] Fisher suggested that whenever attractive males gained a large reproductive advantage, the sexual preferences of females could drive male ornamentation to extremes. When this happened, female preferences would evolve to greater extremes as well because females concerned about reproductive benefits. Evolution will favor super-choosy females for this reason; consequently, both sexes end up in an endless arms race.

[2] See, for example, Andersson (1994), Cronin (1991), and Cavalli-Sforza and Feldman (1981). An exception is Wright (1921), who is among the first to define the measurement for assortative mating.

[3] See, for example, Bergstrom (2001), Fernandez and Rogerson (2001), Kremer (1997), Benabou (1996), Galor and Zeira (1993), Becker and Tomes (1986, 1979), and Loury (1981).

in mate selection is important for evolution/inequality, as posited by Fisher, a better understanding of human mate selection behavior is necessary.

The central question in this paper is: What do we know about human mating behavior in relation to Darwin's mating theory? I test three claims (a) Are females more choosy than males? (b) Are males more differentiated than females? (c) Do more marriageable males marry earlier?[4] We do not observe human mating behavior as easily as that of other animal species, and we do not know whether human behavior can be accounted for by the factors that govern the behavior of animals. Guided by a model that formulates mate choice as a rational decision problem in a decentralized marriage market, I let the data speak for itself.

The model I use is an equilibrium marriage model of mate selection that incorporates agents' preferences, search friction, population heterogeneity, and various economic forces. Mate preferences in terms of potential partners' endowments, such as market earnings and educational attainment, may affect marriageability. Notice that some seemingly useless animal traits from the standpoint of survival, which may be useful as marriageable traits, may not be applicable to the human world. That market traits may also be marriageable traits does seem likely. As explained precisely by Fisher, mate preferences are driven by reproductive benefits, and traits such as high wage or high education may benefit offspring in many ways.

The traditional view of human mate preference claims that women prefer wealthy men and men prefer beautiful women (Ridley, 1995). Recent increases in female educational attainment and participation in the labor force enable females to accumulate wealth. Would the traditional view of mating preferences predict the change in females' economic positions? The speed of meeting affects how intensely the market is sorted.[5] Population heterogeneity affects courtship opportunities, and variation in earnings and education within and between sexes directly affects marriageable traits.

The marriage-search model analyzed and estimated in this paper is in the spirit of Shimer and Smith (2000), Burdett and Coles (1997), and Collins and McNarama (1990), in which agents are *ex ante* heterogeneous (i.e., represented by their types), as well as imperfectly informed about the locations of potential partners.[6] The model

[4] Though I do not test Darwin's assertion on male competition directly, the last question raised here is a way to test the assertion: the "better" sort wins.

[5] Sufficiently speedy meetings give rise to perfect sorting, and a sufficiently slow rate of meetings generates perfect mixing (with respect to traits), other things equal.

[6] The gains of using a search model rather than a stable matching framework (for example, Gale and Shapley (1962) and Roth and Sotomaya (1990)) are two-fold. First, preferences and uncertainty in meeting and separation can be accounted for explicitly in a search framework, which is a more realistic way to think about a marriage market. Second, links between preference and equilibrium allocation can be established.

herein is stationary.[7] There are two states in the market: single and married.[8] Meeting is frictional, random, and sequential.[9] Because partners do not arrive instantaneously, agents choose a range of acceptable potential partners to maximize expected wealth, instead of waiting for ideal partners. Agents' marriageability, that is, types, are revealed upon meeting, whence the decision on whether to match or not is made following a certain optimal selection policy. Matching is monogamous. As in Becker (1973), matching is considered a production opportunity. The costly matching process generates match rents to married couples. Match utility is assumed to be nontransferable. Agents also derive utility from being single. To be consistent with evidence on positive assortative matching, match output takes on economies of scale and complementarity between partners' types. The inflow of agents into the market is governed by an exogenous separation rate.[10]

Given search friction, the utility structure, and the inflow environment, who matches with whom is endogenously determined in the equilibrium. The propensity to marry can be summarized by market friction and the likelihood of agents' acceptances of proposals. The natural rate of singlehood (and hence the sex ratio) is determined by inflows and outflows of the single state; agents' strategies are allowed to affect type distribution.[11] The model offers a rich framework that combines several key structural features of the marriage market and weaves them together to examine marriage waiting time, the measure of singlehood, and the sorting outcome.

The model is estimated using data from the National Longitudinal Survey of Youth (NLSY79) 1979-98. Estimation of the structural parameters of a matching

[7] This means that the marriage offer rate, separation rate, and distribution of types are independent of singlehood and marriage duration, as well as calendar time. This may be unrealistic. For example, partners' arrival rates may decline during singlehood as a result of the stigma that long-term singlehood may have. The motivation for adopting the stationary assumption is basically similar to that in empirical job-search literature. That is, when estimating a non-stationary model, computation difficulties are likely to be more burdensome. So the stationarity assumption is used as a first step in the present study.

[8] To keep the model simple, only two states are considered. Some recent works that focus on individuals' marriage market transitions consider cohabitation as an additional state (Aassve et. al 2001), while others consider divorce as a separate state (Burdett et al. 2002).

[9] Matching may not be random in reality. For example, agents may be sorted by their education investment that has occured prior to a marriage decision. So, agents with different levels of education (say, high school and college) would meet different pools of potential partners, i.e. with different arrival rates based on education choice.

[10] Burdett et al. (2002) develop interesting endogenous separation mechanisms. The cost for this level of generality is that the multiplicity of the model is intractable given available estimation technology. To focus on sorting, separation/divorce is assumed to be exogenous.

[11] This improves on the structural partial marriage models in which singlehood marriageability distribution and sex ratios are exogenous. Typically, men may tend to work in regions favoring their occupations and single women may flock to cities, although these assumptions introduce spurious correlations between sex ratios and hours worked for the former and marital status for the latter. Angrist (2002) offers a nice execution on this front: he uses immigration as an exogenous variation in sex ratios to study its empirical effect on the labor market.

model is done where observed couples are considered as equilibrium outcomes. That said, estimation requires solving the matching model numerically for an acceptable pool of partners for each type of agent. The numerical solution is then nested within a maximum likelihood procedure to estimate structural parameters. Because the probability of who matches with whom and the spell lengths of partner searches are endogenously determined by the optimal strategy, observations on spell lengths of being single and married, as well as individuals' characteristics, provide information that allows identification of structural parameters.

Identification of heterogeneous types is important as a means of blocking unwarranted inferences. However, agents' types are not measurable. Types not only carry a spectrum of observable traits but also contain traits that are unobserved and may be critical in determining who matches with whom. The approach that I propose treats types as a combination of observable and unobservable traits. That is to say, individuals are ranked by mapping a set of observable and unobserved characteristics into a single "marriage index".[12] The estimation procedure also incorporates a flexible classification error model in terms of the marriage index.

To the extent that people are typically associated with potential partners locally, I also consider local marriage markets. Thus, heterogeneity is also treated in terms of age and residential segments. Every segment is a marriage market of its own. In this way my treatment of population heterogeneity allows for within-market (vertical) and between-market (horizontal) heterogeneity.

The results in this paper shed light on various aspects of sexual differences/similarities in marital behavior. Most importantly, the results indicate that males are as choosy as females, while males are more varied in types than females in general. Therefore, Darwin's proposition on female choosiness is not supported.

Both men and women find education to be a more desirable trait for marriageability than wages. Thus the popular notion of women marrying up for income is not supported by evidence. In addition, search efficiency is found to be similar between males and females.

There is a spatial mismatch between men and women: while good (marriageable) men are found in suburbs, good women are mostly located in cities. Interestingly, females in cities tend to have more desirable unobserved characteristics than those in suburbs. While within cities, fmeales exhibit more desirable unobserved traits than males.

The paper helps improve our understanding of how responsive agents' marriage behavior relates to changes in preferences and inequality. Simulation results show a negative impact on sorting if wages were treated as a more desirable characteristic than education. Raising the level of education by 20 percent in general would lead to a more sorted marriage market. Interestingly, a 20 percent increase in residual

[12]A more general technique would be to characteristerize individuals' types directy based on their multi-dimensional characteristics. Although not impossible, this technique would complicate equilibrium matching, and computation would become unrealistic.

inequality has no effect on sorting, while the same increase in wage inequality has a remarkable effect. This indicates that variation in the stochastic aspect of wages is of little importance.

The results not only support Darwin's claim of more male variation in types than females, it also supports Darwins' derived conclusion that highly endowed males marry earlier. My results show that males' marriage hazards are positively associated with their types as well as their wages. However, the mechanism by which this result is obtained differs from that posited by Darwin. In Darwin's world, females choose wealthy suitors, so wealthy males marry earlier, or so peacocks with long tails or cardinals with bright red feather tend to mate more often and have more offspring. This paper finds that selectivity of males and females is alike. The higher hazard rate of high type males is due to higher acceptance probability generated by equilibrium marriage outcomes.[13] This paper is also related to economic development literature. The Malthusian supply of population (1933) is determined by the response of fertility and mortality to changes in income. Malthus posited that poor people marry later in life. So, when wages are low, the population grows more slowly. Results from this paper support Malthus's claim that low earning people have more difficulty in marrying.

Similar to the models in Smith and Shimer (2000) and Burdett and Coles (1997), the model herein predicts positive assortative mating. The present paper differs from those elegant models in the following ways. Smith and Shimer deliver a model that predicts strict assortative mating under a transferable utility and exogenous separation framework. However, 'strict' assortative mating is deemed to be restrictive. Further, because empirical literature offers little guidance in determining the bargaining power between spouses, typical empirical studies assume a fifty-fifty split between spouses, which is to say that match utility is non-transferable.[14] Burdett and Coles develop a non-transferable utility mating model assuming an exogenous inflow of agents. Because marriage history data are readily available, it is more natural to consider separation than an arbitrary inflow of agents who can come from various sources. Therefore, the model in this paper can be considered as a mixture of those in the two previous papers: it is based on non-transferable utility and separation, and has a non-strict assortative mating prediction.

On the scientific front, this paper is similar to many evolutionary studies and psychological literature that assess mate preference in sexual selection and assortative mating (Keller et al. (1996), Andersson (1994), Cronin (1991), Spuhler (1982), van den Berg (1972), and Wright(1921)). Typically, traits are the focus of mate preferences. However, this paper goes beyond existing efforts in that it is capable of incorporating other elements that may affect mating, such as mate selection, unobserved heterogeneity, search friction, and economic inequality. The present paper weaves all these elements into an equilibrium framework of marriage.

[13] See Burdett and Coles (1997) for a prove.

[14] See, for example, Eckstein and Wolpin (1995).

On the technical front, estimations of continuous time discrete-state equilibrium search models such as the one in this paper have recently received considerable attention (for example, Bontemps et al. (1999), van den Berg and Ridder (1998), Eckstein and Wolpin (1995)). The maximum likelihood estimation method employed here is similar to that in Wong (2003) and Eckstein and Wolpin (1995), in that it is based on solving agents' reservation values and using the numerical solution in a likelihood function. But the estimation procedure in the present paper offers a technical breakthrough, in that it considers observed marriages as equilibrium outcomes and presents a means to estimate structurally a steady state assortative mating model, taking into consideration not only the numerical solution of agents' optimal strategies of acceptance on each side of the market, but also observed and unobserved heterogeneity and agents' strategies in affecting singlehood distributions.

An alternative technique in marriage model estimation consists of discrete-time discrete-state dynamic programming models. For example, Van Der Klaauw (1996) studies marital choice and female labor supply choice. More recently, Aassve et al. (2001) and Pierret (1996) use a proportional hazard model to study transition (from home) to marriage. The novelty in this paper is its focus on the equilibrium in a two-sided framework that matches people assortatively. This task may not be easily implemented in typical dynamic programming models or in a reduced-form proportional hazard model.

Unlike many empirical works that use cross-sectional marriage data (e.g. Boulier and Rosensweig (1984) and Keeley (1979, 1977)), this paper uses individual marriage history data. To study marriage choice carefully, one has to pay attention to the pool of people who remain single: ignoring single people (right-censoring) biases parameter estimates. Besides, when only data with currently married agents are used, the elapsed marriage time exceeds zero. This means that wages and education at the time of interviews may not accurately reflect characteristics at the time of marriage. Here, I use pre-marital wage data, which is an improvement over reliance solely on post-marriage wage information because the division of labor within families may affect choices of occupation and labor efforts, i.e., post-marriage wages may be correlated with marital income. Further, the structure of panel data allows a direct application to the dynamic nature of the model, thereby allowing direct testings of the model's assumptions, and hence, its usefulness.

The matching model is outlined in section 2. Section 3 contains data extraction and descriptions. The estimation method and derivation of the likelihood function of the matching model are discussed in section 4. Section 5 contains results of the estimation. Section 6 examines marriage hazards. Section 7 concludes.

2 Two-Sided Matching

2.1 Assumptions

Time is continuous, and there are two groups of infinite-lived risk-neutral agents, men and women. At each point in time, all agents are in one of two states: single or married.[15] Only single agents search for marriage partners. For simplicity, search cost is assumed to be zero. Let the partner arrival rate for single men (women) be λ_m (λ_w), which is governed by a Poisson process. Upon meeting, agents decide whether or not to match. If a match is formed, it dissolves with a constant flow probability (Poisson rate) $\delta > 0$, and agents flow back to the single pool.[16] If no match is formed, an individual searches again.

Agents are *ex ante* heterogeneous with respect to their types x.[17] The types of two potential partners are revealed upon meeting. Let there be J types for men (i) and women (j), where J is a positive finite integer bounded away from ∞. Assuming discrete types instead of a continuum of types is attractive for reasons of flexibility and for computational ease. The range of types is bounded by $[\underline{x}_i, \overline{x}_i]$, where $\underline{x}_i$ and $\overline{x}_i$ indicate the infimum and supremum of its support. Let the proportion of type x_i single agents be $s(x_i)$ and the cumulative distribution function be $S(x_i) = \sum_{k=1}^{i} s(x_k)$. Because agents' marriage strategies as well as the number of agents who get married and those who separate affect the pool of single agents in the market, the distribution of single agents is endogenous.

While an agent is single, instantaneous utility is the real value of the agent's type. When an agent is married, instantaneous utility is assumed to be an equal split of match production $x_i x_j$.[18] The utility structure implies that $\underline{x}_i >= 2$.[19] In sum, the market is described by the structural parameters $< \lambda_m,\ \lambda_w,\ \delta >$.

2.2 Value Functions

A single agent chooses a range of acceptable types of potential partners with the objective of maximizing his expected discounted value in the future utility stream. Consider a type x_i single agent who discounts future income at rate β. The value of singlehood is his instantaneous utility x_i and the expected benefit of marriage follows

[15] Because there are only 2 states, single refers to unattached or non-married agents, i.e., never-married, separated or divorced, or widowed.

[16] This assumes no entry of new singles. Alternative channels for the entrance of new singles into the market over time include cloning (Bloch and Ryder, 2000), exogenous inflows (Burdett and Coles, 1997), and endogenous inflows (Pissarides, 1990).

[17] Type is essentially a single index. See section 4 for details.

[18] That says the model is one with non-transferable utility.

[19] The infimum $\underline{x}_i$ ($\underline{x}_j$) must be at least as large as 2 to satisfy the incentive constraint for marriage: that match utility is at least as large as utility while single, $\frac{x_i x_j}{2} >= x_i$ ($\frac{x_i x_j}{2} >= x_j$). Should this constraint fail to hold, a fraction of each sex will not marry.

an optimal policy if a partner of type Y is realized, given that a partner has arrived. If T_0 is the waiting time for the first marriage, the flow value of being single is

$$V(x_i) = E\left(\int_0^{T_0} x_i e^{-\beta t} dt + e^{-\beta T_0} \max\{W(x_i, Y), V(x_i)\}\right), \tag{1}$$

where $W(x_i, Y)$ is the expected discounted value of marriage with a random partner of type Y. Note that the constant flow can be written as

$$\int_0^{T_0} e^{-\beta t} dt = \left[-e^{-\beta t}/\beta\right]_0^{T_0} = \left(1 - e^{-\beta t}\right)/\beta. \tag{2}$$

Because partners arrive according to a Poisson process with intensity $\lambda_m > 0$, $T_0 \sim \exp(\lambda_m)$, i.e., the density of the waiting time is

$$f(t) = \lambda_m e^{-\lambda_m t}, t > 0, \tag{3}$$

the exponential distribution with arrival rate λ_m. The expected value of the random discount factor in (1) is

$$E\left(e^{-\beta T_0}\right) = \int_0^{\infty} e^{-\beta t} f(t) dt = \frac{\lambda_m}{\beta + \lambda_m} \int_0^{\infty} (\beta + \lambda_m) e^{-(\beta + \lambda_m)t} dt = \frac{\lambda_m}{(\beta + \lambda_m)}. \tag{4}$$

Combining with (2), this allows calculation of the expected value of the integral in (1) as

$$E \int_0^{T_0} x_i e^{-\beta t} dt = x_i E\left(1 - e^{-\beta t}\right)/\beta = \frac{x_i}{\beta}\left(1 - \frac{\lambda_m}{(\beta + \lambda_m)}\right) = \frac{x_i}{(\beta + \lambda_m)}. \tag{5}$$

Because partners' arrivals are distributed independently of the preceding waiting times, (1) can be written as

$$V(x_i) = \frac{x_i + \lambda_m E \max\left[W(x_i, Y), V(x_i)\right]}{(\beta + \lambda_m)}. \tag{6}$$

The *ex post* value of marriage is made up of the match utility and the value of remaining single due to an exponential random separation. Because separations occur at rate δ, a marriage dissolves at $T_1 \sim \exp(\delta)$. The value of marriage is

$$W(x_i, x_j) = E\left(\int_0^{T_1} \frac{x_i x_j}{2} e^{-\beta t} dt\right) + E(e^{-\beta T_1}) V(x_i). \tag{7}$$

From (5), the first term in (7) is $\frac{x_i x_j}{2(\beta+\delta)}$. Moreover, $E(e^{-\beta T_1}) = \frac{\delta}{(\beta+\delta)}$.Therefore, (7) can be recast as

$$W(x_i, x_j) = \frac{x_i x_j}{2(\beta + \delta)} + \frac{\delta V(x_i)}{(\beta + \delta)}. \tag{8}$$

A steady state pure strategy for a type x_i agent is to choose a set of agents A_i with whom x_i is willing to match, $A_i = \{x_j | W(x_i, x_j) >= V(x_i)\}$. The lowest type with which x_i is willing to match is determined by a reservation policy defined by: $W(x_i, R_i) \equiv V(x_i)$, where R_i represents the reservation type of type x_i. While x_i can determine with whom he desires to match, he also needs to be desired by potential partners. Define x_i's matching set to be $\mathcal{M}_i \equiv A_i \cap \{x_j | x_i \in A_j\}$, which contains the set of women types to whom he proposes and who are willing to match with him. A match of a pair of agents (x_i, x_j) is mutually acceptable if each party is willing to match with the other, $x_i \in A_j$ and $x_j \in A_i$, or $x_j \in \mathcal{M}_i$.[20]

Combining equations (6), (8), and the reservation policy, the reservation-partner-type is the solution to the following equation

$$R_i = 2 + \frac{\lambda_m}{\beta + \delta} \sum\nolimits_{x_j \in \mathcal{M}_i} (x_j - R_i)\, s(x_j). \tag{9}$$

The solution is unique because the left-hand side of equation (9) is increasing in R_i and the right-hand side decreasing. Because the situation is symmetric between men and women, the reservation type for women satisfies

$$R_j = 2 + \frac{\lambda_w}{\beta + \delta} \sum\nolimits_{x_i \in \mathcal{M}_j} (x_i - R_j)\, s(x_i). \tag{10}$$

2.3 Steady State Accountings

2.3.1 Steady State Singlehood

The singlehood type distribution, $s(x_i)$, is endogenous in this model. Let u_m and u_w denote the fraction of singlehood for men and women respectively. Let $L(x_i)$ denote the exogenous population distribution of types, $L(x_i) = \sum_{k=1}^{i} l(x_k) = \Pr(X < x_{i+1})$, where $l(x_i)$ represents the corresponding probability density function. Types are distributed according to L, independently of spells of being single.

The law of motion for $s(x_i)$ is determined by the difference of the inflow and outflow of singlehood for every type of agents. The density of type x_i married agents is $[l(x_i) - s(x_i)u_m]$, with matches dissolving at rate δ. So, the inflow into singlehood is $\delta[l(x_i) - s(x_i)u_m]$. The marriage hazard of type i agents is

$$h_i(\lambda_m, s(x_j)) = \lambda_m \sum\nolimits_{j \in \mathcal{M}_i} s(x_j). \tag{11}$$

So, the outflow from singlehood is $h_i(\lambda_m, s(x_j))s(x_i)u_m$. The steady state flow of singlehood for type x_i men is made up of match destruction and match creation flows:

$$\delta[l(x_i) - s(x_i)u_m] = h_i(\lambda_m, s(x_j))s(x_i)u_m. \tag{12}$$

[20] $x_i \in \mathcal{M}_j$ implies $x_j \in \mathcal{M}_i$.

The steady state flow of singlehood for type x_j women is made up analogously. So, for J discrete types, there are $2J$ equations and $2J$ unknowns: u and $(J-1)$ singlehood type fractions for men and women respectively.

An increase in δ unambiguously raises the steady state singlehood rate, u_m or u_w. An increase in the partner arrival rate directly reduces the singlehood rate, but it indirectly raises the singlehood rate through its positive effect on the reservation type that reduces agents' acceptance probability.

2.3.2 Aggregate Accounting

Steady state also satisfies an aggregate accounting condition for meeting:

$$\lambda_w = \frac{u_m}{u_w}\lambda_m, \tag{13}$$

where u_m/u_w is the steady state sex-ratio, endogenously determined using (12) for each sex. (13) reflects that the number of single females whom single males meet $(u_m\lambda_m)$ must be the same as that of single females meeting single males $(u_w\lambda_w)$ in steady state. If there are more single males than females, the arrival rate of partners for single females is higher.

2.4 Equilibrium

A steady state search equilibrium requires that (i) every single individual selects his(her) own partner type to maximize the expected net benefit flow attributable to the choice of partner, given the optimal choices made by all other single individuals, (ii) each single individual finds a potential partner acceptable, and (iii) all singlehood rates are in steady state.

In other words, for all $i, j = 1, ..., J$, a set of joint matching strategies $\{A_i, A_j\}$, or $\mathcal{M}_i$, two singlehood densities $s(x_i)$, $s(x_j)$ and the natural rate of singlehood u_m, u_w that follow the balanced flow in (12) for each type of men and women respectively, and the aggregate accounting condition (13) are Nash equilibrium solutions to the non-cooperative stationary game of matching.

The equilibrium solution is a two-dimensional graph. Positive assortative matching, i.e., a positive relation between reservation types and agents' own types, is the predicted equilibrium outcome.[21]

[21] This result is driven by the underlying specifications of agents' output, which are positive utility when single and increasing returns to scale and complementarily between partners' types when married.

3 Estimation Strategy

The goal is to estimate the likelihood of a type i agent marrying a type j agent. The assumptions underlying the theoretical model of section 2 allow endogenous derivation of the equilibrium for who matches with whom, and the distributions of singlehood and marriage duration. Therefore, a natural estimation strategy is a likelihood analysis.

3.1 Solution Method

The model does not permit an analytical solution, but results can be numerically solved in a straightforward manner. The numerical complexity arises because the calculation of equilibrium matching sets requires solving the reservation equations and satisfying the two accounting conditions for each type of agents. In solving the steady state equilibrium matching sets, a matching algorithm is used (see appendix). Essentially, given a set of initial parameters, I solve for the endogenous elements in the model: $\{R_i, R_j\}$, $\{s(x_i), s(x_j)\}$, $\mathcal{M}_i$, where $i, j = 1, ..., J$, λ_w, and u_m. The numerical solutions are then applied to the likelihood function (see below). The parameter estimates are obtained when the logarithm of the likelihood function is maximized.

3.2 Estimation Method

3.2.1 Between-Market Heterogeneity

I consider between-market heterogeneity by assuming that there are separate marriage markets (or submarkets) for different groups of individuals. That separate markets for different groups of individuals exist due to the fact that agents' association with potential partners tends to be local. Agents with different characteristics such as age are assumed to have different fundamental parameters. To incorporate this type of hetergeneity, the model can be estimated separately for each marriage market, using only individuals that belong to the particular marriage submarket.[22][23]

In what follows, I segment the marriage market into two age groups (Age1=14-18 and Age2=19-22) and two groups sorted according to geographical locations (City1=not reside in a city, City2=reside in a city).[24] Age dummies used as stratification variables may be inadmissible because age is not a time-invariant personal characteristic. But

[22] The segmentation assumption precludes cases where individuals from one segment compete with those from another segment. It would be a challenge to build a model allowing for competing segments.

[23] Alternatively, one can assume that deep structural parameters in the model $< \lambda_m, \delta >$ vary over different marriage markets in a consistent way. That said, one can estimate the parameters using data on all markets simultaneously, assuming that $< \lambda_m, \delta >$ are log-linear functions of $\mathbf{z}, \lambda_m = \exp(\beta_1' \mathbf{z}_m)$, and $\delta = \exp(\beta_2' \mathbf{z}_m + \beta_3' \mathbf{z}_w)$,where $\mathbf{z}_m$ and $\mathbf{z}_w$ respectively denote a vector of observable characteristics for husbands and wives.

[24] Because of the small sample size, I do not consider (age1 and city1) as a segment.

I use age dummies because age may strongly affect agents' preferences. So, results based on age stratification may be informative with respect to sorting. Whether an individual resides in city is also considered because it measures population dispersion, which can be used as a proxy for search cost.

3.2.2 Within-Market Heterogeneity

Within-market heterogeneity is given by agents' types (marriageability), which summarize mate preferences. Agents' types are unobserved. One way to treat this problem is to consider it as unmeasured. A standard approach is to allow for a finite mixture of types, each comprising a fixed proportion. This nonparametric approach is proposed in Eckstein and Wolpin (1999), Keane and Wolpin (1994), and Heckman and Singer (1984). In the latter two studies, Monte Carlo integrations are sought to evaluate integrals for multidimensional state space. But because I am interested in quantifying how wage inequality and human capital affect sorting, I allow measured characteristics to affect agents' types.

I model agents' types as a parametric function of observable characteristics and unobserved heterogeneity. I consider individuals' education e and logarithm of wage w as observable marriageable endowments.

Agents on each side of the market are assumed to have identical valuations for endowments of potential partners of the opposite sex. I rank individuals and generate discrete categories according to the following steps:

(a) Generate a marriage index z as a weighted average of e and w

$$z = \alpha e + (1 - \alpha) w + v, \tag{14}$$

where $\alpha \in [0, 1]$ is a scaler parameter and v represents unobserved heterogeneity. Parameter α can be interpreted as the price of spousal demand of education. A high α characterizes agents who place a high value on education as a marriageable characteristic relative to wage. I assume that v has a discrete distribution with three unknown points of support. The family of discrete distributions is attractive for reasons of flexibility as well as for computational ease.[25] Let the three points of support be denoted by $v_1 < v_2 < v_3$, and the corresponding probabilities by $\exp(p_i)/\left[\sum_i \exp(p_i)\right]$, with normalization $p_3 = 0$.

The advantage of using a weighted average in (14) as opposed to other functional forms such as Cobb-Douglas is that such an arrangement offers a simple exposition so that the true effect of education on mate preference can be calculated (see discussion below.)

(b) Take the range of the corresponding order statistics of z and discretize it into J equal partitions, where J is a positive finite integer. For example, if $J = 10$ and the sample size is N, $z_{(1)} <= ... <= z_{(N)}$ is partitioned into deciles.

[25] I experimented with additional points of support, but during the ML procedure these sometimes converged to existing ones.

(c) The set of z within each $i-th$ interval is mapped to x_i following the mapping:

$$x_i = median\left(z_{Li} < z <= z_{Hi}\right), \tag{15}$$

where z_{Li} indicates the lowest z that makes a type i individual, and z_{Hi} indicates the highest z that makes a type i individual. The real-valued x_i represents a type i individual, which is a piece-wise constant within the corresponding $i-th$ interval of z.

Note that α does not represent the true effect of returns to education on marriageability because it has an indirect effect through wage. Consider a linear log wage equation for males,

$$w_m = \mathbf{z}'_m \beta_m + \epsilon_m, \tag{16}$$

where $\mathbf{z}_m$ contains typical human capital variables and ϵ_m is an idiosyncratic shock.[26] Suppose β_{em} represents the coefficient of males' schooling. Inserting (16) into (14) and collecting terms, the true effect of education on marriageability is $\alpha^*_m = \alpha_m + (1-\alpha_m)\beta_{em}$. For females, the log wage equation is

$$w_w = \mathbf{z}'_w \beta_w \Phi + \sigma\phi + \epsilon_w, \tag{17}$$

where ϕ and Φ are respectively the standard normal pdf and cdf. The true effect of education on marriageability for females is $\alpha^*_w = \alpha_w + (1-\alpha_w)\beta_{ew}\Phi$.

To assess the impact of residual inequality on sorting, I generate wage realizations using data $\mathbf{z}_m$ and $\mathbf{z}_w$, the OLS estimates of β_m, β_w, the predicted residuals ϵ_m and ϵ_w, and the consistent estimates of ϕ and Φ, which come from a probit estimation.

Though agents are positively sorted for age, age does not go into the marriage index. As mentioned above, age makes the model non-stationary. If age is used as agents' type in the model, we will also get a finite life problem, which contradicts the standard assumption in most of the search literature of the infinite horizon. But empirically, one can study the importance of the effects of age on sorting by conditioning the estimation on age.[27]

3.2.3 The Likelihood Function

The structural parameters to be estimated are $< \alpha_m, \alpha_w, \lambda_m, \delta, v_1, v_2, v_3, p_1, p_2 >$. The model is identified from data that consist of a panel where some individuals are single with duration t_0 (identifies λ_m), married with duration t_1 (identifies δ), and where a couple's wage and education at first marriage w_s and e_s, respectively, for $s = m, w$ (identify α_s).

[26] The vector $\mathbf{z}$ contains an agent's experience, its squared, education, regional dummies, number of children, and the unemployment rate of one's resident state. Because interactions between the labor market and marriage market are not jointly modelled, marriage has no impact on wage.

[27] For example, see van den Berg and Ridder (1998).

Consider a type x_i man who is single at first interview. Let t_{0b} be the elapsed single duration and t_{of} the residual single duration so that $t_0 = t_{0b} + t_{0f}$. Let t_{0b} and t_{0f} be i.i.d. and have an exponential distribution with parameter $h_i(\lambda_m, s(x_j)) = \lambda_m \sum_{j \in A_i} s_j$, which represents the hazard rate of marriage. Let D_{0b} (D_{0f}) denote a binary variable that equals one, if it is known that the elapsed (residual) duration exceeds a certain value, i.e., left-censored (right-censored), and zero otherwise. Conditioned on being type x_i, the individual contribution of single duration until and including the time of exit into marriage or censoring is

$$L_{0i} = h_i(\lambda_m, s(x_j))^{1-D_{0b}+1-D_{0f}} \exp\left[-h_i(\lambda_m, s(x_j))t_0\right], \tag{18}$$

where $t_0 > 0$.

Events occurring after exit from singlehood are independent of the events up to exit. Therefore, their probability is independent of the likelihood of being single. The event immediately following type x_i's single duration is the realization of whom to match with. This contribution is used to identify α_m and α_w. This event is given by the joint density of acceptance $f(x_i, x_j | x_j \in M_i)$, which equals the product of the density of an accepted type for each sex, $f(x_i | x_i \in M_j)$ $f(x_j | x_j \in M_i)$, due to the independent nature of agents' acceptance decisions.

Let $I(x_j \in M_i)$ be an indicator function equaling one if a type x_j woman is contained in the marriage set of a type x_i man. The probability that the type x_i man matches with a type x_j woman is the fraction of type x_j women out of all types of women acceptable to a type x_i man,

$$f(x_j | x_j \in \mathcal{M}_i) = \frac{s(x_j) I(x_j \in \mathcal{M}_i)}{\sum_{j=1}^{J} s(x_j) I(x_j \in \mathcal{M}_i)}. \tag{19}$$

Accordingly, that for type x_j women is,

$$f(x_i | x_i \in \mathcal{M}_j) = \frac{s(x_i) I(x_i \in \mathcal{M}_j)}{\sum_{i=1}^{J} s(x_i) I(x_i \in \mathcal{M}_j)}. \tag{20}$$

Conditional on the realized partner type, marriage duration t_1 has an exponential distribution with parameter δ. If $D_{0f} = 1$, I do not follow the agent any longer. Let $D_1 = 1$ if t_1 be right-censored, and equal zero otherwise. Because the acceptance density is independent between men and women, if $D_{0f} = 0$, a type x_i and type x_j agents' likelihood contributions to events between entering marriage and separation equals

$$L_{1ij} = f(x_i | x_i \in \mathcal{M}_j) f(x_j | x_j \in \mathcal{M}_i) \delta^{1-D_1} \exp(-\delta t_1), \tag{21}$$

where $t_1 > 0$.

The total type x_i individual contribution to the likelihood function for a respondent who is single at the time of the first interview equals the product of (14) and (17), which describes the odds of each type x_i man who initially is single matching with a type x_j partner with a marriage offer, and subsequently undergoing an exogenous marriage dissolution:

$$L_{ij} = L_{0i} L_{1ij}^{(1-D_{0f})}. \tag{22}$$

Let n denote each observation; since observations of each type of men are independent, the likelihood function is

$$L = \prod_{n \in (i,j)} L_{ij}, \tag{23}$$

where with $i = 1, ..., J$, $j = ., 1, ..., J$.[28] Given $< \alpha_m, \alpha_w, \lambda_m, \delta, v_1, v_2, v_3, p_1, p_2 >$, $\{R_i, R_j\}$ can be solved using (9) and (10). The arrival rate of partners for females, λ_w, and the singlehood type distributions, $s(x_i)$, $s(x_j)$, are also solved in the equilibrium as a fixed-point from the accounting conditions. The likelihood function must nest within it the numerical solutions from the matching model to solve for the acceptance set of each type of individual.

The log likelihood is maximized using the Cauchy fast simulating annealing algorithm, directly adopted from Corana (1987).[29] Consistent standard errors are obtained using bootstrap.[30]

3.2.4 Classification Error

Incorporating classification errors in estimation is necessary for at least two reasons. First, allowing for classification errors prevents the log likelihood from underflowing if a transition from singlehood to marriage occurs with a partner type that is not acceptable by the model (i.e., within agents' marriage sets). Second, the support of type distribution depends on the parameters of the model, implying that ML estimates of parameters are sensitive to errors in classifying agents (for example, see Wolpin (1987), van den Berg and Ridder (1998)). Given the discrete (types) setup of the matching model, a flexible classification error model developed in Wong (2003) is adopted. In what follows, I outline the classification error model.

I assume that an agent's type equals true type plus an error term, which is independently distributed across marriage spells and across individuals, and which is independent of all other random variables in the model. Let k and l denote the true type for i and j respectively. Let the classification errors for type i and j agents be denoted as v_1 and v_2 respectively. So, $i = k + v_1$ and $j = l + v_2$. Notice that the values of each support point of the classification errors are known. So, I only need to estimate the distribution of classification errors. To reduce the parameter space, I consider classification errors as the distance between the true type and the observed

[28] A missing value of j represents an observation of a single male.

[29] This algorithm has been tested to be faster than the typical Boltzman simulating annealing procedure in statistical science.

[30] I use standard bootstrap drawing N observations with replacement.

type. If $d(k,i) = |k-i|$ is the distance between the true type k and the observed type i, then $q(d)$ denotes the classification-error probability with distance equal to $d(k,i) = |v_1|$.

Further, I assume 10 types of agents and a symmetric classification error structure. That is, the probability of misclassifying an individual is the same for any i and k with the same distance, $q(d) = q(d')$ for any $|k-i| = |k'-i'|$. For example, the probability of misclassifying a type 5 to a type 3, say, equals that of misclassifying a type 7 to a type 9. The consequence of assuming symmetry is to reduce the parameter space from 90 to 9 for each sex.

Given these assumptions, I solve for the classification error probabilities using linear algebra. Because the linear programming problem has less than full rank, I obtain five parameters of classification-error probabilities, $\mathbf{e}_s =< e_{s1}, e_{s2}, e_{s3}, e_{s4}, e_{s5} >$ for each sex $s = m, w$, and $\varepsilon_1 = < e_{m0},\ e_{m1},\ e_{m2},\ e_{m3},\ e_{m4},\ e_{m5},\ e_{m4},\ e_{m3},\ e_{m2},\ e_{m1} >$, where $e_{s0} = 1 - (2e_{s1} + 2e_{s2} + 2e_{s3} + 2e_{s4} + e_{s5})$. So, the dimension of the numerical integral of the classification error in the likelihood contribution is further reduced from 9^2 to 5^2.

For all samples of men and women with $i = 1, ..., J$, $j = ., 1, ..., J$, the likelihood function incorporating classification errors is

$$L_c = \prod_{n \in (i,j)} \sum_{v_1 = i-10}^{i-1} \sum_{v_2 = j-10}^{j-1} L_{(i-v_1)(j-v_2)} q(|\varepsilon_2(\mathbf{e}_w)|) q(|\varepsilon_1(\mathbf{e}_m)|), \tag{24}$$

subject to $e_{s1}, e_{s2}, e_{s3}, e_{s4}, e_{s5} > 0$, and $2e_{s1} + 2e_{s2} + 2e_{s3} + 2e_{s4} + e_{s5} <= 1$, for $s = m, w$.

4 Data

4.1 The Sample

The data for this analysis are from the NLSY79 youth cohort. 1979-1998 cross-sectional and supplemental samples consist of 11,406 respondents, who were between the ages of 14 and 22 in 1979. The samples are core nationally representative random samples. Interviews have been conducted yearly since 1979.

To estimate the matching model, marriage history data are needed. Specifically, I use data for the age at first marriage and marriage duration, wages, and education. Because my focus is on assortative mating at first marriage, I use only the first marriage spell, even though longer marriage histories are available.

Among the respondents, 10,207 were single in 1979. Each year respondents reported their marital status. If a respondent remained in the same marital status for more than one interview, that marital status is listed multiple times. I follow respondents who started as singles in 1979 throughout the twenty-year period, and reduce multiple spells to one observation for each spell. The sample is thus reduced from 183,726 to 23,891 spells.

To obtain marriage histories, I need to know what respondents were doing each year over the entire twenty-year period. Spells with missing start or stop dates cause breaks in marriage histories. For example, some respondents failed to married, became non-responsive and then married. Excluding these observations, 12,335 spells are left. As I do not distinguish between separation and divorce, whichever occurred first will count as an interrupted spell for marriage. Using this restriction, 10,262 spells are left. Because only single and first marriage spells are used, the sample is further reduced to 9,573 spells. Some reports contain erroneous observations, for example, separation occurred before marriage. Excluding these observations, 9,509 spells are left.

The NLSY79 also contains information on changes in marital status, the start and end days of marriage. But these reports are not always consistent with reported yearly marital status. So care must be taken to obtain accurate records of the time marriage and/or separation occurred. Sometimes the start year of marriage occurred one year prior to the year of marriage reported in marital status, and/or the age at first marriage was one year less than the age corresponding to the year of marriage reported in marital status. This can happen if the interview was carried out before the respondent's birthday that preceded his/her marriage. I cross-check agents' birthdates and interview dates to determine the exact year in which marriage occurred.

Having determined the age at first marriage, I generate singlehood duration data by taking the difference between the age at first marriage and spousal search starting time, assumed to be 15.[31] I made this assumption because search duration can only be partially observed, since the elapsed single duration t_{0b} is unknown, $s = m, w$.[32] Therefore, if t_0^* is the stopping time of singlehood and c is the censoring time, the completed spell of search duration is $t_0 = t_{0b} + t_{0f} = \min\{t_0^*, c\} - 15$. The elapsed single duration t_{0b} is determined by the length of time respondents were single at the first interview, and the residual single duration t_{0f} is determined by the length of time they remained single after the first interview.[33]

The duration of marriage, $t_{1,}$ is defined as the number of years a couple stays married before or until the censored time, whichever comes first. A number of marriage spells in the NLSY79 had years of duration equal to zero, i.e., respondents were

[31] First, age 15 is the official Census definition for the marriageable age (see Statistical Abstract 1996 for details.) Second, evidence from the Census reveals that in 1970, 99 percent of women were married at or after age 18 and men at or after age 20. In 1990 the corresponding ages were 20 and 22 for women and men respectively.

[32] The initial condition problem is solved by Chamberlain (1979) using a bayesian technique, in which the random effect distribution is conditioned on forward recurrence information. Ondrich (1985) controls for heterogeneity assuming that both unemployment and employment spells have Weibull Distribution with parametric unobserved heterogeneity. Recent treatments make use of indirect inferences. Results from an exponential model and Cox's Proportional Hazard model reveal that there is a significant heterogeneity in the duration of being single in my sample. Heterogeneity in my model is captured by the acceptance selection of each individual's type, assuming that $\lambda > 0$.

[33] By analogy with the renewal literature, these durations are also known as the backward T_{ob} and forward T_{of} recurrence times respectively.

married at the censoring time. Treating these spells as having a duration of one year may artificially produce duration dependence even when none was present. In what follows, I maintain the assumption that durations are exponentially distributed and exclude zero duration. This leaves me with 9509 spells. Based on the estimate of hazard rate obtained under the exponential specification, I test whether the data can reject the exponential specification.

During the course of singlehood, those who remained in hospital or incarcerated are considered to be inactive in the marriage market. Excluding those leaves me with 9,383 spells.

The identification of one's spouse is obtained by determining whether a family member existed (among eleven to fifteen of them) who reported himself/herself as a "spouse" to given respondents. There were thirty-one codings of the same sex between respondents and spouse or partner; these observations are deleted. Missing records for spouses' age and education are also deleted. Erroneous reports of ages of spouses can be found. For example, spouses' ages are coded as 1. I exclude spouses' ages that fall below 15. Imposing these restrictions, 8,875 spells are left.

Wages and education are taken as of the year of respondents' marriage or the censored year if single. I restrict my sample of respondents those who reported the first job they performed, working at least twenty hours a week, and lasting longer than two weeks. Unknown tenure or hours worked per week are treated as missing and deleted. Extreme time or pay rates were also deleted (For example, some reported a weekly wage of 66 cents, and an hourly rate of 26,000 dollars.) I cross-check all time and pay rate responses against the upper and lower bounds collected for men of the same education and race from the Current Population Survey (CPS) every year.[34] Because there are no records of race for spouses, I cross-check all pay rates with the bounds from the CPS every year based on spouses' sex and education only. Those whose wages did not fall within admissible ranges are treated as missing and deleted. I use weekly wages in constant (1990) dollars. After excluding inadmissible wage reports, following selection criteria, and including only white males, 1,133 respondents are left. 37 percent of spouses' ages or education data are missing. After deleting these observations from the sample, I obtain a final total of 796 respondents, out of which there are 231 spells of censored single and 565 transitions to marriage, of which 228 spells are transitions to separation or divorce. For each of these spells, I have data on duration, censoring code, and personal characteristics (and spouses' characteristics if married) including wages and education.

Among respondents who were married, about one third of spouses did not work. There may be a potential correlation between marriage and labor supply choice. However, wages for spouses were recorded in previous year's wage earnings instead

[34] I use the 5th and the 95th percentiles of weekly wages from the March outgoing rotation groups for each year. I treat the top five percent weekly wages as missing because of the thin tail that often covers a large range on the wage scale. Sample restrictions are the same as those described in the text.

of the current year, which is actually desirable because it reduces the marital labor supply effect. This is the benefit of using panel data; the correlation between marriage and labor supply choice can be reduced substantially. To address the issue of selection bias, one could directly estimate the female labor supply.[35][36] In what follows, I predict wages for all women who had zero wages taking into account selection bias, using Heckman's two-step method (1976).[37]

To check how representative the sample is, I compare it with the 1990 Census data, an economy-wide baseline (see below).

4.2 Sample Description

Table 1 contains sample characteristics for white males and their spouses and white males who were single. Married men had lower mean education levels than their spouses. Wage data tell the conventional story: men earn more than women. There are more variation in males' wage and education than females'.

Note that comparing the (log) wage data for married and single males reveals that married men earned less than single men, who in general had higher average education levels than married men. These characteristics arise because the age of single respondents in the sample is on average higher than the age of married respondents (recorded at their first marriages). Thus the difference in earnings could be due to the usual suspects: experience, life cycle effects, and so on. As such, taking agents' wages at face value may hide true wage potential because of the life cycle effect. For example, a 36 year-old man is expected to earn more than a 26 year-old. But this does not necessary make the 26 year-old man less marriageable, because it is the present value of lifetime earning that counts. One can standardize wage or use an estimated lifetime wage as in Boulier and Rosensweig (1984) for estimation. I attempt the latter approach in estimation; my results show no qualitative difference in estimates.

Table 1. Sample Characteristics of White Males, NLSY 1979-98

[35] But inserting such a mechanism into the currrent framework adds a substantial computation burden. Because the mechanism to solve a basic equilibrium marriage model is not fully understood, I leave this task for future research.

[36] Alternatively, the sample could be split into two subsamples – one with both spouses working, the other with only males working – that are analyzed separately. But this would create a problem of overcounting the singlehood spells for men. For example, subsetting the sample to include only spouses who worked would give me 39 percent of males remaining single; using a sample with traditional families (with males working only) would give me 53 percent of males remaining single. The same pool of single males will be used in each subsample to avoid the false appearance that many men remained single who actually did not.

[37] To correct for the selectivity bias, I estimate a participation probit using the standard Heckman procedure. The regressors are individuals' education, experience and its squared, regional dummies, unemployment rate, and the number of children.

	All	Age1	Age2	City1	City2
Married					
wage	6.026	6.025	6.028	5.868	6.081
	(.485)	(.491)	(.480)	(.425)	(.490)
education	13.027	12.855	13.247	12.610	13.172
	(2.236)	(2.296)	(2.141)	(2.072)	(2.275)
wife's wage	5.600	5.595	5.605	5.341	5.671
	(.462)	(.466)	(.457)	(.370)	(.462)
wife's education	13.149	12.997	13.344	12.836	13.258
	(2.186)	(2.293)	(2.028)	(2.024)	(2.232)
Single					
wage	6.122	6.150	6.077	5.944	6.157
	(.348)	(.465)	(.505)	(.554)	(.458)
education	13.515	13.723	13.189	12.590	13.703
	(2.570)	(2.544)	(2.592)	(2.256)	(2.595)

Table 2. Sample Singlehood/Marriage Durations of White Males, NLSY 1979-98

	All	Age1	Age2	City1	City2
Number of Observations	796	459	337	185	611
Stock of Non-Married	459	227	182	96	363
Marriage					
Fraction Censored	0.597	0.572	0.628	0.610	0.592
Mean Duration, Male	10.953	10.011	12.058	11.944	10.597
Standard Deviation	3.740	3.395	3.833	3.641	3.718
Number of Observations	565	318	247	146	419
Singlehood					
Fraction Censored	0.290	0.307	0.267	0.211	0.314
Mean Duration, Male	10.211	9.597	11.00	8.856	10.683
Standard Deviation	4.178	4.003	4.274	3.699	4.236
Number of Observations	231	141	90	39	192

Descriptive statistics on singlehood and marriage durations are given in table 2. The stock of non-married individuals includes both single and divorced respondents. In this sample, 71 percent of respondents ended up marrying. Older respondents and those who resided in cities had more difficulty in getting married than younger and suburban respondents. Unlike older respondents, city people also had difficulty in maintaining their marriages. About 60 percent of marriages remained censored.

Empirical survival rates (Kaplan-Meier estimates) decline with the duration of singlehood (not shown). The general declining shape of the hazard function reflects a pure heterogeneity model of singlehood duration.

Table 3. Sample Characteristics of White Males, IPUMS 1980

	All	
Married	Mean	S.D.
wage	6.114	0.675
education	13.403	2.690
wife's wage	5.663	0.661
wife's education	13.753	2.563
N	466702	
Single		
wage	5.716	0.759
education	9.381	2.103
N	7368407	

Note: the sample characteristics are weighted by household weight

To check how representative the sample is, I compare it with the 1980 census, tabulated in table 3.[38] The sample contains non-institutional white males whose ages are between 16 and 41, whose first marriage concurred in 1980, with labor market characteristics as selected in the NLSY. The census characteristics resemble those in the NLSY: married males had higher wages but lower educational levels than their spouses. The difference between the two samples is that single males earned less and were less educated than married males in the census. But this is explained by the different data structure mentioned above.

5 Empirical Results

Table 4 presents parameter estimates for the basic model without unobserved heterogeneity, while the corresponding estimates for the model with unobserved heterogeneity in types x are contained in table 5.[39] The parameters are estimated for the entire sample as well as for sample subsets obtained by stratification for age and residential location as measured at the first interview in 1979. Given the parameter estimates, I calculate estimates of α^*, $\lambda/(\beta+\delta)$, $\underline{x}$, $\overline{x}$, $E(x)$, $Var(x)$, $E[W(x,y|x)]$, and sex ratio for each sample segment. Unobserved heterogeneity and classification errors have been integrated out in all calculations. The sample averages of these estimates are listed in table 6.

5.1 Parameter Estimates

Parameter estimates under the unobserved heterogeneity model demonstrate moderate shifts over the model without unobserved heterogeneity. The inclusion of unobserved heterogeneity in x improves the fit of the model. When going from the model

[38] Because education data are grouped in 1990 census, I use the 1980 census.

[39] The logarithm of the likelihood function is estimated setting the discount rate at $\beta = 0.05$. The results are robust to various values of discount rates. For example, I estimated the model using $\beta = 0.3$ and 0.75 and found that the qualitative results remained unchanged.

without unobserved heterogeneity to the model in which x has a discrete distribution with 3 points of support (which amounts to adding 5 parameters), the log likelihood increases 22 points. Because the estimates of null classification error probability are higher in the model with unobserved heterogeneity, agents' type in the model with unobserved heterogeneity are closer to their true types. With these observations, the model with unobserved heterogeneity in x is the preferred specification in the discussion below.

Table 4. Maximum Likelihood Estimates, no Unobserved Heterogeneity

	All		**Age1**		**Age2**		**City1**		**City2**	
	M	W	M	W	M	W	M	W	M	W
α	.9617	.8495	.9472	.8499	.8349	.8045	.9698	.8027	.8005	.8488
λ	.0631	.0642	.0657	.0668	.0526	.0523	.0872	.0885	.0626	.0632
δ	.0472	–	.0514	–	.0339	–	.0411	–	.0478	–
e_0	.7769	.9443	.7337	.9487	.7606	.7261	.7527	.9843	.7309	.9157
e_1	.0001	.0260	.0003	.0233	.0805	.0990	.0269	.0068	.0583	.0378
e_2	.1052	.0002	.1234	.0001	.0193	.0232	.0963	.0004	.0732	.0013
e_3	.0061	.0001	.0091	.0001	.0183	.0101	.0003	.0003	.0016	.0002
e_4	.0001	.0015	.0003	.0021	.0008	.0041	.0001	.0001	.0006	.0028
e_5	.0001	.0001	.0001	.0001	.0016	.0011	.0001	.0005	.0017	.0001
N	796		459		337		185		611	
log L	-4765.5294		-2704.8024		-2132.841		-1206.0569		-3614.2385	

Note: $e_{s0} = 1 - (2e_{s1} + 2e_{s2} + 2e_{s3} + 2e_{s4} + e_{s5})$, $s = m, w$.

Table 5. Maximum Likelihood Estimates, Unobserved Heterogeneity

	All		**Age1**		**Age2**	
	M	W	M	W	M	W
α	.8448	.8463	.9549	.8182	.6885	.8298
	(.0481)	(.0323)	(.1140)	(.0292)	(.1048)	(0655)
λ	.0652	.0650	.0649	.0650	.1117	.1137
	(.0023)	(.0023)	(.0104)	(.0107)	(.0244)	(.0246)
δ	.0478	–	.0564	–	.0364	–
	(.0027)		(.0026)		(.0030)	
e_0	.7792	.9469	.7660	.9609	.7820	.8219
e_1	.0005	.0248	.0007	.0163	.0720	.0857
	(.0048)	(.0164)	(.0172)	(.0080)	(.0307)	(.0314)
e_2	.1040	.0004	.1056	.0004	.0260	.0016
	(.0057)	(.0053)	(.0121)	(.0046)	(.0268)	(.0052)
e_3	.0054	.0001	.0104	.0003	.0103	.0006
	(.0058)	(.0011)	(.0061)	(.0009)	(.0079)	(.0036)
e_4	.0002	.0011	.0002	.0024	.0005	.0003
	(.0048)	(.0035)	(.0021)	(.0018)	(.0029)	(.0016)
e_5	.0006	.0003	.0002	.0003	.0004	.0017
	(.0017)	(.0016)	(.0041)	(.0020)	(.0057)	(.0031)
v_1	-2.525	-1.805	-2.421	-1.658	-2.913	-2.603
	(1.220)	(.8525)	(1.193)	(.2838)	(.5724)	(1.608)
v_2	-1.916	5.732	-0.132	1.621	-1.893	8.666
	(.8908)	(1.146)	(.0246)	(.9382)	(.7409)	(2.259)
v_3	-2.769	-0.197	-0.062	-1.964	-3.076	-0.055
	(1.342)	(.8065)	(.0446)	(1.111)	(1.751)	(.0595)
p_1	4.780	4.293	4.798	3.987	4.385	4.131
	(.2858)	(.3101)	(.0173)	(.2447)	(.2259)	(.2166)
p_2	1.013	1.025	.8059	.8069	1.919	1.409
	(.3075)	(.3902)	(.0931)	(.1223)	(.1362)	(.0848)
N	796		459		337	
log L	-4743.4117		-2695.6775		-2116.9013	

Note: Bootstrapped standard deviation of the parameter estimates in parentheses

$e_{s0} = 1 - (2e_{s1} + 2e_{s2} + 2e_{s3} + 2e_{s4} + e_{s5})$, $s = m, w$.

Table 5. (continues)

	City1		City2	
	M	W	M	W
α	.9755	.9589	.8013	.7158
	(.0482)	(.1632)	(.0148)	(.1392)
λ	.0972	.0987	.0595	.0601
	(.0118)	(.0118)	(.0030)	(.0030)
δ	.0400	–	.0513	–
	(.0048)		(.0044)	
e_0	.8055	.9843	.8206	.9395
e_1	.0003	.0072	.0040	.0243
	(.0133)	(.0197)	(.0170)	(.0475)
e_2	.0961	.0001	.0851	.0038
	(.0224)	(.0301)	(.0152)	(.0077)
e_3	.0007	.0001	.0003	.0009
	(.0048)	(.0094)	(.0059)	(.0036)
e_4	.0001	.0001	.0001	.0012
	(.0094)	(.0058)	(.0041)	(.0017)
e_5	.0001	.0001	.0004	.0001
	(.0063)	(.0094)	(.0127)	(.0041)
v_1	-.0825	-1.474	-2.971	.4058
	(.9012)	(.9018)	(1.357)	(.1649)
v_2	-2.776	-2.972	.5236	.8095
	(.7619)	(1.055)	(.1510)	(.2010)
v_3	-1.903	-2.014	-2.304	9.266
	(1.093)	(.5931)	(.7956)	(.6841)
p_1	3.998	4.484	4.088	4.280
	(.1978)	(.2159)	(.1253)	(1.309)
p_2	.8010	1.098	1.421	1.086
	(.2546)	(.3624)	(.2771)	(.3350)
N	185		611	
log L	-1195.5184		-3601.1215	

Note: Bootstrapped standard deviation of the parameter estimates in parentheses

$e_{s0} = 1 - (2e_{s1} + 2e_{s2} + 2e_{s3} + 2e_{s4} + e_{s5})$, $s = m, w$.

Education has a greater impact than wage on agents' desirability as marriage partners, as shown in all segments in row 3 of table 5.[40] Interestingly, despite the importance of education, it is less intensely desired as a marriageable trait for older males than younger ones, and agents who reside in cities appear to have less desire for education compared to those who reside in suburbs. It appears that males' preferences vary substantially with age, and city dwellers have different mate preferences than

[40]Even though education is a relatively more important marriageable trait, quantifying marriageability using education alone is incorrect. Results from estimation in Wong (2003) indicate that the presence of both wage and education gives a more significant description of marriageability.

suburbanites. True returns from education for marriageability, α^*, are 0.8541 for men and 0.8634 for women in the sample (table 6).

Is there a sexual difference in mate preference? I re-estimate the model by restricting mate preference, that is, $\alpha_m = \alpha_w$ (results not shown). I then perform a likelihood ratio test to obtain a test statistic $S = -2 (\triangle \log L)$, which has a χ^2 distribution of one degree of freedom. Except for the overall sample and the suburban segment (City1), all segments demonstrate a significant difference in mate preference, with test statistics ranging from 3.97 to 6.02.

Men and women have similar rates of contact with potential partners (row 4, table 5), implying that the estimated sex ratio, u_m/u_w, is close to unity (column 9, table 6). This result is an expected outcome from the model because meeting and matching is assumed to be one-to-one.

The way in which deep transition estimates vary with age appears to be in accordance with intuition. Age2 agents have a higher partner arrival rate and if married their marriages last longer than the Age1 cohort. This is because agents' search time is assumed to depend on an identical spousal search starting age, an older agent has more "experience" in the marriage market than a younger one, and thus contacts more potential partners in random matching. Agents' marriage behavior varies substantially among geographical locations. Basically, the results paint a gloomier picture for agents residing in cities: they have a more difficult time contacting potential partners, and once marriage occurs, it is more likely to break apart.

The effective discount rate ($\lambda/(\beta + \delta)$), or search efficiency, increases with age and is higher for suburban agents (column 3, table 6). All else equal, this indicates that older people and suburban people tend to be more selective. If the inverse of search efficiency tends to zero, i.e. if the number of meetings generated during the singlehood spell is large, agents meet at high speed and competition among agents causes strict assortative mating, i.e. mating with the same types of partners.

Table 6. Model Characteristics, Unobserved Heterogeneity

	α^*	$\frac{\lambda}{(\beta+\delta)}$	$\underline{x}$	$\overline{x}$	$E(x)$	$Var(x)$	$E[W(x,y\|x)]$	sex ratio
All								
Men	.8541	.6667	2.742	15.545	8.564	4.373	223.399	.9768
Women	.8634	.6656	3.249	16.887	9.633	3.533	384.575	
Age1								
Men	.9576	.6100	4.221	18.582	10.939	5.682	262.723	.9937
Women	.8384	.6109	3.200	16.406	9.465	3.821	397.704	
Age2								
Men	.7072	1.2928	2.720	12.582	6.759	3.506	170.519	1.0128
Women	.8487	1.3160	3.472	13.786	7.511	3.614	287.598	
City1								
Men	.9770	1.0800	5.805	20.580	12.147	4.543	273.192	.9862
Women	.9635	1.0656	3.531	13.246	10.422	5.359	436.027	
City2								
Men	.8132	.5874	2.958	14.005	8.784	4.628	161.721	1.0052
Women	.7473	.5903	3.506	16.124	10.963	2.844	388.676	

The estimated proportion of classification errors shows that the probability of no classification error for men and women is high. This result stems from the large equilibrium marriage sets (see subsection 5.3).

In general, females tend to have more desirable unobserved characteristics than males in cities. Geographically, females in cities appear to have more desirable unobserved characteristics than those in suburbs. Comparing the logarithm of likelihoods in tables 4 and 5 shows that unobserved heterogeneity is important for older and city-dwelling agents. That is to say, wage and education alone play small roles for seasoned agents as well as for city dwellers.

Table 6 shows that while the younger cohort has a higher average and variation in types than the older group, females have higher average types than males in the older cohort. Interestingly, good (high type) men and women do not live in the same location. While good men are found in suburbs, good women are mostly located in cities. While males do not vary much in types geographically, females are more alike in cities than in suburbs.

So, is Darwin right? Are males are more heterogeneous than females? I test the null hypothesis $H0 : Var(x_m) > Var(x_w)$ against the one-sided alternative $H1 : Var(x_m) <= Var(x_w)$. I simlulate the distribution of $Var(x_m)$ and $Var(x_w)$ by resampling and generate T-statistics. At significance level equaling 0.05, results show that all but Age2 and City1 segments do not reject the greater variation in males' types.[41]

Females have a higher value of marriage than males (see column 8 of table 6). The value of marriage for the older cohort and city dwellers is remarkably lower than for younger and suburban agents of either sex. This indicates that those agents will

[41]I also calculate F-statistics based on the bootstrapped variance. Results do not reject the null (marginally) at a 0.01 significance level for the same data segments.

be less selective.

Next, I perform a sensitivity check on the specification of the econometric model. Different specifications of the marriage index are used. The estimates using a Cobb-Douglas specification (not reported) are close to identical to those reported here. However, if an exponential function is taken over the linear form that is used here, certain estimates would differ quite a bit.[42] Because an exponential function generates an artificially skewed type distribution, the majority of agents are concentrated in the lower support. Note that singlehood duration depends partly on λ and partly on acceptance probability, which entails type distribution. To compensate for low acceptance probability due to rare opportunity, λ must be sufficiently high. While the arrival rate rises substantially, the estimates α and δ are only slightly affected by such functional form.

Within the present linear framework, λ is low. The population type distribution is not as skewed as in the exponential case. As it is not so difficult to get a high type partner, λ diminishes. I should emphasize that even though the estimate of λ differs substantially between the exponential and the non-exponential specification, the predicted equilibrium from each specification yields the same sorting outcomes.

5.2 Goodness of Fit

Duration data are the basic data elements considered for model fitness. Table 7 compares the actual and predicted values of singlehood and marriage duration. The average predicted singlehood duration seems to fit the data quite well. It is expected that marriage duration will be under-estimated because the exogenous separation process predict too large a separation probability. To see how well the parameter estimates match the nationwide age at first marriage, I draw on census data (1970-80).[43] Using census data and model estimates, I predict the average singlehood duration and compare it with the empirical value.[44] Because census data are sampled from the stock rather than the flow, the singlehood duration is distributed Gamma with parameters 2 and the inverse of the hazard rate. Table 8 shows that the model yields fairly close predictions.

I also compare the actual and predicted stock of non-married individuals (table 7). Because there are only two states in the model, single and married, the estimated stock of singlehood equals the stock of non-married respondents in the data. Again, the small values of predicted stock are associated with a too large a separation rate.

[42] See Wong (2003) for an example.

[43] Respondents in the sample contain those who first married in the particular census year. Other sample selection criteria are similar to those in the NLSY. The 1990 census does not contain data on age at first marriage, whereas the CPS collects the age at first marriage data in 1994 only. Other data sets such as the Marriage Details from the Vital statistics do not contain wage data and so I am unable to calculate marriageability for each agent that affects their marriage hazards.

[44] The average age of first marriage for respondents in the 1970 and 1980 census is respectively 28.55 and 28.01.

Table 7. Model Predictions

	$E(T_{0m})$	$E(T_1)$	u_m
All: Actual	10.211	10.953	0.5766
Predicted	11.034	8.442	0.4637
Age1: Actual	9.5970	10.011	0.4946
Predicted	10.795	7.5830	0.5134
Age2: Actual	11.000	12.058	0.5401
Predicted	11.823	10.233	0.4252
City1: Actual	8.8560	11.944	0.5189
Predicted	9.3340	9.7600	0.3178
City2: Actual	10.683	10.597	0.5941
Predicted	11.045	7.9550	0.4871

Table 8. Comparison of the Predicted Age at First Marriage with Census Data

	1970	1980
Actual	13.55	13.01
Predicted	14.49	13.76

While predicted means are useful as guides to how well the model captures certain features of data, it is constructive to conduct formal tests of model fit. The assumptions of Poisson arrival rates imply that singlehood and marriage durations should be distributed with intensity parameters $\lambda[s(M_i) - s(R_i)]$ and δ respectively, where i represents a type i agent.[45] To check how well the exponential model fits the data, I perform a formal test by fitting a Weibull model to the duration data: the purpose is to test the slope of the shape parameter ρ in the Weibull model. Under the null hypothesis of an exponential model, the slope of the shape parameter $\rho = 1$.

Results in table 9 show that the exponential model fits the singlehood spells quite well (columns 4 to 6). The shape parameter in singlehood spells is fairly close to one and the asymptotic confidence interval is right on the line for most data segments. So, the assumption of exponential spousal search times is not rejected by the data. Note that this result is a direct consequence of taking unobserved heterogeneity in the hazard rate into account (and subsequently integrating it out). For example, the estimate without conditioning out unobserved heterogeneity in the overall sample is $\rho = 0.5379$.

Table 9. Specification Tests For Exponential Search and Match Times

[45] The transition rate to marriage is obtained after conditioning out unobserved heterogeneity in types.

	ρ	95% lower limit	95% upper limit
All: Singlehood	0.9076	0.7794	1.0358
Marriage	0.9596	0.7896	1.1296
Age1: Singlehood	0.9128	0.8083	1.0173
Marriage	0.9686	0.7972	1.1402
Age2: Singlehood	0.8633	0.7581	0.9685
Marriage	0.9183	0.7135	1.1231
City1: Singlehood	0.9107	0.7790	1.0424
Marriage	1.0004	0.7364	1.2644
City2: Singlehood	0 .9235	0.8420	1.0049
Marriage	0.9514	0.8327	1.0871

Results for marriage spells show that the standard errors of ρ are large. These results raise suspicion about the model's fitness even though the asymptotic confidence interval covers one and the estimates are right around one. Because the estimates are smaller than one (except the suburb segment), marriage durations exhibit a decreasing hazard, that is to say, marriage tenure is negatively associated with the separation hazard. Such duration dependence may be spurious, and unobserved heterogeneity may be required to improve the fit of the model. Alternatively, the separation process may be too simple and extensions in model may be necessary.

In sum, the model fits the spousal search data well and raises suspicions about marriage duration data. The result indicates that further investigation is necessary. In particular, including unobserved heterogeneity in the separation hazard or describing more complicated separation processes such as endogenous match destruction, would seem to be necessary.

5.3 Who marries Whom?

According to Darwin, females are more choosy than males. Yet recent evolutionary biologists find evidence from many animal species that refute Darwin's theory. What do we know about stratification in the equilibrium marriage market of the human world? Overall, the marriage market is divided into two disjoint classes. Figure 1 plots equilibrium marriage sets using the entire dataset. Men and women are asymmetric in their selection, with men being choosier than women. The first marriage class contains male agents of types 3 to 10 and female agents of type 4 to 10. Because types 4 to 10 women are willing to accept type 3 males, type 3 males climb up to the first class. The second marriage class contains the remaining types. This result shows a stark contrast to Darwin's claim. A plausible explanation for female non-choosiness is that there are not many appealing males out there (column 6, table 6).

Women become more choosy in the age 14-18 segment than the overall sample, making symmetric marriage sets. Such selection may be due to the type distribution of single males being more spread than the overall sample, and males being more marriageable on average.

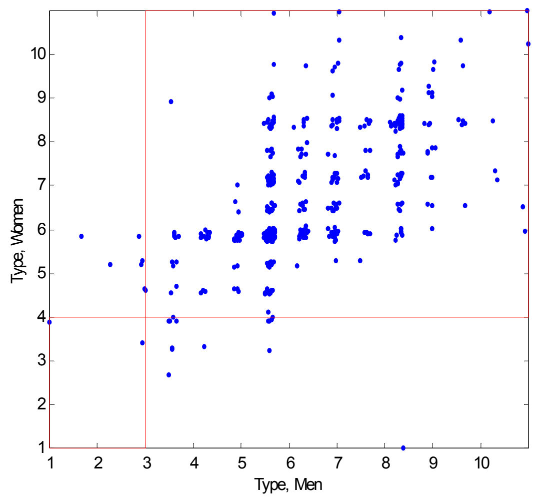

Figure 1: The Equilibrium Marriage Sets for All

The sorting pattern for the age group 19-22 is interesting. Clearly, both males and females are less picky than the overall sample and the younger cohort. As shown in table 5, search efficiency is higher for older than younger cohort: other things equal, more sorting should occur. The result from the Age2 segment shows a remarkably high partner arrival rate despite less assortative mating when compared with the Age1 sample, which shows about a 50 percent lower partner arrival rate. This indicates that other forces work against the search efficiency element in sorting.

In the Age2 segment, males are remarkably similar to one another and they are less marriageable compared to the Age1 segment. The mean gender difference for singlehood type distribution is also lower. As such, when the chance of drawing a high type male is slim and when there is little mean difference in type, there is little point in holding out for higher type partners, so females become less selective despite a high partner arrival rate. Moreover, table 6 reflects that the value of match for the Age2 cohort is about 65-72 percent of that for the younger cohort. If the outside option of singlehood is low, selective sorting is unlikely. Male agents are also less picky because unlike those in the younger group, they have similar (if not worse) marriageability as compared with female agents in the older group. Because of their lack in appeal in the marriage market, male agents would tend to be less choosy than the younger cohort, even though they encounter potential partners twice as frequently.

Interestingly, the sorting patterns are the same between the two geographical settings, despite the large differences in partner arrival rates in each geographical setting. Again, search efficiency seems to play a small role in sorting people between geographical settings.

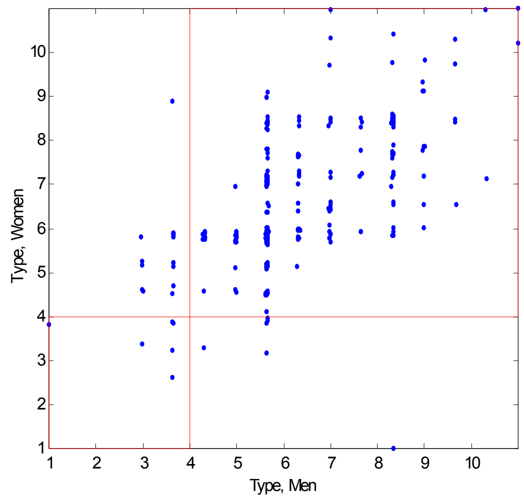

Figure 2: The Equilibrium Marriage Sets for Age 14-18

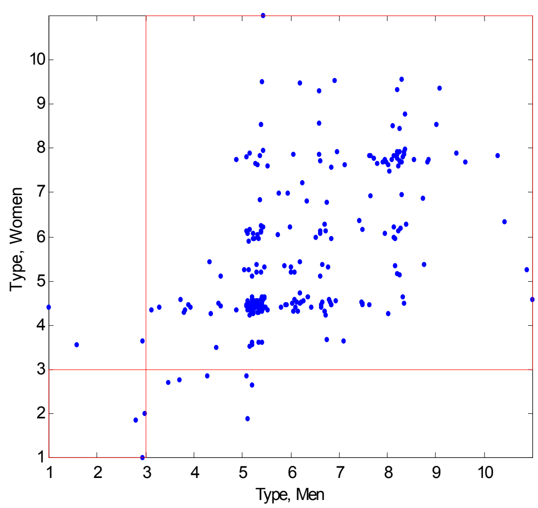

Figure 3: Equilibrium Marriage Sets for Age 19-22

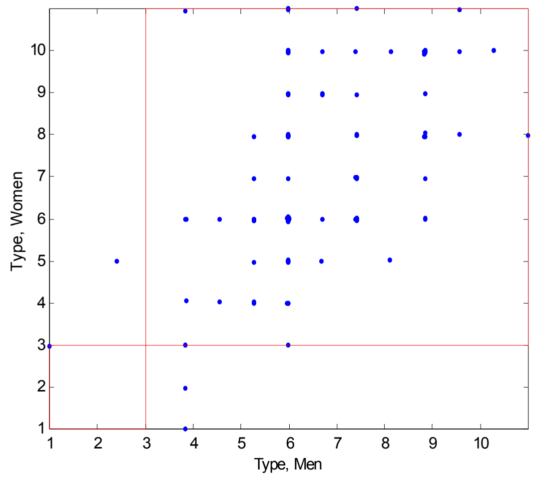

Figure 4: Equilibrium Marriage Sets in Suburbs

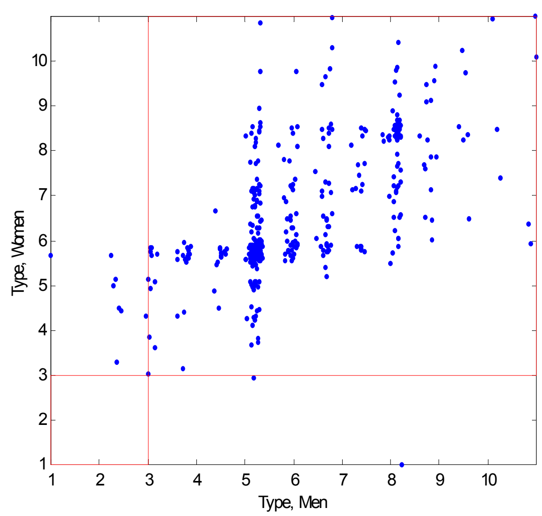

Figure 5: Equilibrium Marriage Sets in Cities

An explanation for the sorting pattern in suburbs is that of type distribution differences. When males face females with a lower mean types, they become less selective. Females seem to be affected by variation in males types more than the converse for males. Females face a more homogeneous pool of males compared with themselves. Knowing that they would have fewer chances to draw a high type male, even though high type males have an impressive level of marriageability, females simply respond by being less picky.

In cities, males are not as marriageable as females on average. This, coupled with a low-arrival rate of partners, means males are not selective. Relatively well-to-do females are also not selective, partly because there are not many good picks out there (a large gender difference in mean types) and partly because there is little meeting.

In sum, these results appear to indicate that the level and distribution of types play integral roles in selective mating.

Next I test whether or not females are more choosy than males. The null hypothesis is $H0 : R(x_j) > R(x_i)$.[46] I simulate the distribution of the reservation types for males and females by resampling, and then form a pivotal statistic (T-statistic) for each type in each sample segment. Results do not reject the null at all significance levels for all segments of data. These results do not support Darwin's sexual selection theory of female choosiness.

5.4 Effects of Changes in Preferences and Inequality

To evaluate the implications of the estimates in table 5 for individual mating selection behavior, it will be useful to analyze in more detail the influence of some variables, and in particular wage distribution, on marriage selection.[47] I study what the model would predict if (i) agents had the same desire for wage as they do for education, and thereby reduced their preferences towards education, (ii) the arrival rate of female partners were 50 percent higher, (iii) the population type distribution were equalized between sexes, and (iv) inequality were reduced. Simulation results are presented in table 10.

Conventional correlation indicates that agents are more sorted in education than in wages. Results when placing wage as a more marriageable characteristic support the conventional finding that agents become much less sorted (table 10a). Because of the increase in acceptance probability, in general, the duration of singlehood for males and females would be reduced, and the equilibrium stock of singlehood would be lower. The overall sample as well as all segments are responsive to changes in preferences.

An increase in females' arrival frequency would give rise to a more sorted market

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[46] Strictly speaking, I should test the difference between males' and females' range statistics.

[47] It would be interesting to quantify the relative contributions of these factors on sorting. However, the task appears to be difficult because the model is highly nonlinear and because there is no obvious metric to judge the relative size of alternative changes that would induce assortative mating.

for the overall sample as well as agents stratified geographically, but would have no effect on the segments stratified by age. If males and females had the same population distribution, this would have no or only trivial effects on agents sorting pattern and marriage waiting time.

Table 10a. Effects of Changes in Model Parameters

		All	**Age1**	**Age2**	**City1**	**City2**
baseline*	$E(T_{0m})$	11.0344	10.7951	11.8230	9.3340	11.0450
	u_m	0.4637	0.5134	0.4252	0.3178	0.4871
	sorting	2;4-10,3-10	2;4-10,4-10	2;3-10,3-10	2;3-10,3-10	2;3-10,3-10
$\triangle\alpha$	$E(T_{0m})$	10.8694	9.0363	12.0004	9.2065	10.7802
	u_m	0.4421	0.4748	0.4176	0.3276	0.4692
	sorting	1;2-10,1-10	1;2-10,1-10	1;3-10,1-10	1;2-10,1-10	1;1-10,1-10
$\triangle\lambda_m$	$E(T_{0m})$	6.3345	10.7809	7.5496	5.5323	6.9404
	u_m	0.3249	0.5173	0.3551	0.2271	0.3387
	sorting	~Age1*	no change	no change	~Age1*	~Age1*
$L(x_m)$	$E(T_{0m})$	11.1998	11.5357	12.3733	8.4969	11.7964
$= L(x_w)$	u_m	0.4577	0.5289	0.4015	0.3089	0.4986
	sorting	~Age1*	no change	no change	no change	no change

N.B.: The first entry in row 4 'sorting' represents the number of classes, then the range of first class for males and females respectively.

Numerous studies have shown that relative wages within sex groups have widened while those between the sexes have narrowed (e.g., Katz and Murphy, 1992). Suppose wage represents types of agents. An increase in relative wages within sexes can be reflected by an increase in the variance of type distribution. When the population becomes more heterogeneous, agents become more picky, other things equal. Consequently, more sorting will occur. If the male wage dispersion is higher than that for females, women will become more selective because of the higher chance of getting a good draw.

A decrease in the relative wages between the sexes can be caused by a decrease in the mean type difference between sexes. The empirical wage distribution of men first-order stochastically dominates that of women. If men face women with lower mean types, men have tougher luck to match with high type women. The expected match benefits are reduced, and men become less picky. On the other hand, when women face men with higher mean types, women have more opportunities to meet with higher type men, and this raises their expected match benefits. Consequently, women become more selective. So, as long as men's distribution first-order stochastically dominates that of women, men tend to be less selective.

To understand how the model predicts the specific role of changes in various inequality measures, I perform the following experiments. First, I raised the level of wages by 20 percent while keeping all moments constant. I repeat raising the level of education by 20 percent, reducing gender mean wages by 50 percent, and increasing the residual wage inequality and overall wage inequality (90/10) by 20 percent.[48][49] Results are shown in table 10b.

Because education is a more desirable marriageable trait, changes in the level of education have a larger effect than changes in wage level. An increase in the level of education by 20 percent in general would lead to a more sorted marriage market. An increase in the wage level or a reduction in the gender wage gap would have less effect on sorting.

Interestingly, changes in residual inequality have no effect on sorting while changes in wage inequality have remarkable effects. These results indicate that variation in the stochastic part of wages is not as important as variation in the deterministic part of wages.

Raising the level of wages and education, as well as wage inequality, and the narrowing of gender mean wage gaps, appear to have more impact on the sorting outcomes for the older cohort than they do for the younger group. People from different geographical locations have similar responses to changes in inequality.

Table 10b. Effects of Changes in Inequality

		All	**Age1**	**Age2**	**City0**	**City1**
baseline*	$E(T_{0m})$	11.0344	10.7951	11.8230	9.3340	11.0450
	u_m	0.4637	0.5134	0.4252	0.3178	0.4871
	sorting	2;4-10,3-10	2;4-10,4-10	2;3-10,3-10	2;3-10,3-10	2;3-10,3-10
$\triangle$**levels of**	$E(T_{0m})$	10.7218	10.6676	14.0254	10.7312	12.5111
wages	u_m	0.5183	0.5174	0.5619	0.3667	0.4824
	sorting	no change	no change	2;3-10,4-10	~Age1*	no change
$\triangle$**levels of**	$E(T_{0m})$	10.1535	10.4983	13.7427	10.7629	12.3247
edu.	u_m	0.4607	0.5061	0.4302	0.3634	0.5097
	sorting	~Age1*	no change	2;3-10,4-10	~Age1*	~Age1*
$\triangle$**gender**	$E(T_{0m})$	11.3812	11.3511	13.9976	10.7312	7.9674
mean wage	u_m	0.4577	0.5289	0.4866	0.3667	0.3324
	sorting	no change	no change	2;3-10,4-10	~Age1*	2;3-10;4-10
$\triangle$**resid. ineq.**	$E(T_{0m})$	11.3812	10.6627	11.8912	9.4272	11.6981
both	u_m	0.4577	0.5174	0.4299	0.3140	0.4795
	sorting	no change	no change	no change	no change	no change
$\triangle$**ineq.**	$E(T_{0m})$	10.5031	10.5182	12.0174	10.7619	12.2430
both	u_m	0.4733	0.5071	0.4351	0.3635	0.5063
	sorting	~Age1*	no change	2;3-10,4-10	~Age1*	~Age1*

[48] Because variance in education has remained relatively constant in the past few decades, I focus on wage variation in affecting type distribution.

[49] Results below refer to an increase in (residual or wage) inequality for both males and females. Raising inequality for either sex gives rise to slightly less sorting outcomes.

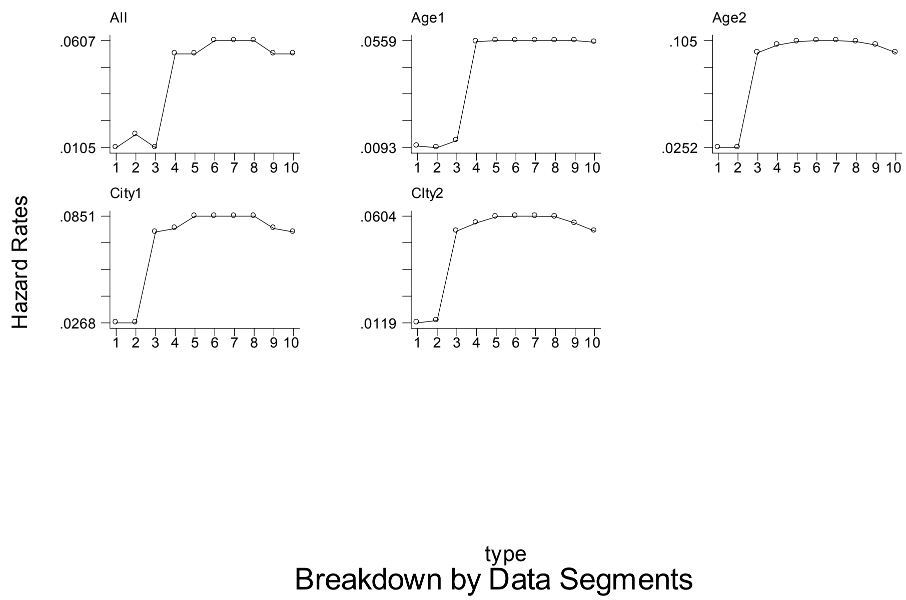

Figure 6: The Relation Between Predicted Hazard Rates and Types

6 Marriage Hazard

Darwin posits that if highly ornamented males outcompete less ornamented males, highly ornamented ones are more prone to mate earlier. Similarly, Malthus (1933) and Becker (1973) also posit that high-wage males are likely to marry earlier than low wage people. In this section, I explore how marriage hazard varies with type and wages.

Given the parameter estimates, I calculate estimates of the hazard rate of marriage for each type of agent. Figure 6 show the relation between predicted hazard rates and types. A general positive relation is shown, though middle-type agents may have a higher rate. For example, from the overall sample, type 7 agents have 0.0061 times higher rate than the highest type agents, whose rate equals 0.0545.

What is the relationship between marriage hazards and earnings? To answer this question, I rearrange men and women by wage decile and quintile in the sample. Each wage group can contain more than one type of agent. So I calculate a weighted hazard rate for each wage group. The results are depicted in figures 7-8. Interestingly, when wage is partitioned as decile (figure 7) the lowest type agents have fairly high hazard rate, except for the young cohort which demonstrates a general upward trend. Recall from table 6 that there are more good men in suburbs than cities, and these men seem to have some difficulty in getting married compared with lower-type males (with 0.01 difference in rate). When taking wage in quintile, figure 8 shows a general

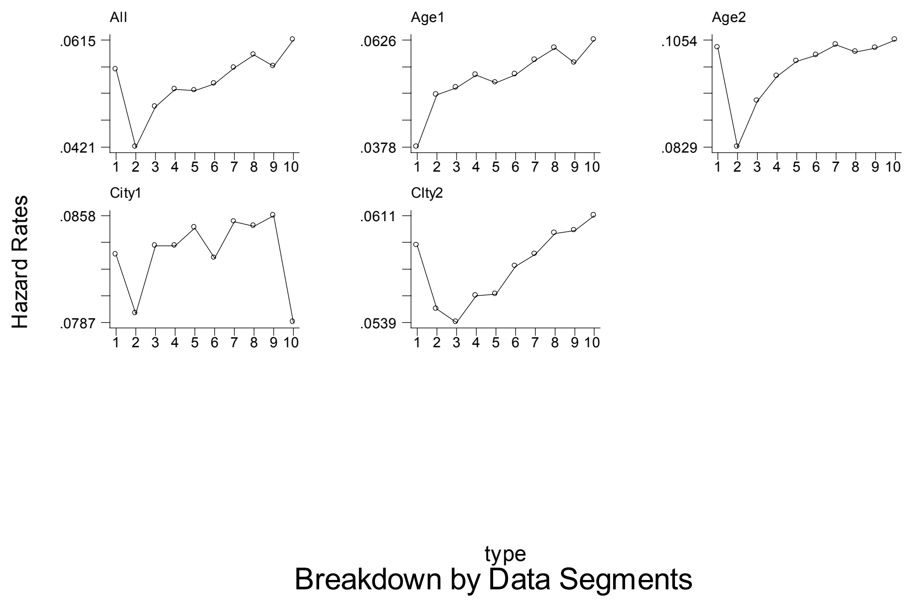

Figure 7: The Relation Between Predicted Hazard Rates and Wage Decile

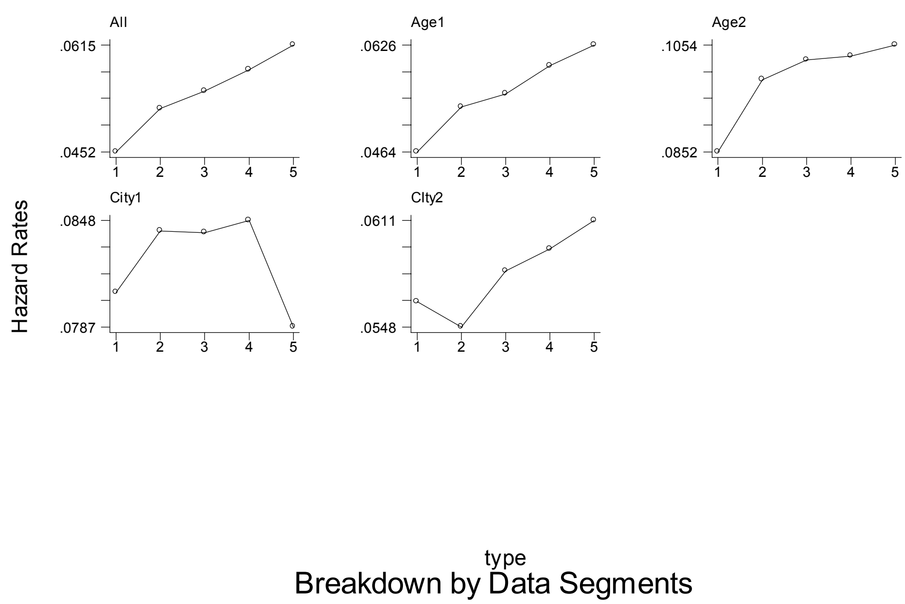

Figure 8: The Relation Between Predicted Hazard Rates and Wage Quintile

monotone hazard rate, except for suburban males.

In general, high-wage men tend to escape from singlehood faster than their low-wage counterparts. This result supports Malthus's (1933) claim and Aassve et al.'s (2002), Pierret's (1996) and Keeley's (1979) findings.

7 Conclusion

For the first time in an empirical study, marriage market search and assortative matching are modelled as the outcome of optimal choices made by both men and women. Although the nature of the mating model is that of monogamy, not all individuals of mating age become coupled, so the model allows considerable sexual selection. To estimate the model, a straightforward procedure is developed that allows ranking of agents, computation of equilibrium marriage acceptance sets, incorporation of unobserved heterogeneity and classification errors in a direct manner. The model is shown to fit the data reasonably well in terms of singlehood search behavior.

The estimates indicate that both males and females find education to be a more desirable trait than wage in predicting marriageability. This result indicates that the popular hypothesis of women marrying up for income is not supported. Interestingly, good (high type) men and women do not live in the same location. While good men are found in suburbs, good women are mostly located in cities.

Females tend to have more desirable unobserved characteristics than males, particularly those who reside in cities. People from cities appear to have more desirable traits than people from suburbs. The older male cohort seems to have less desirable unobserved characteristics than the younger male cohort, while spouses of older males demonstrate more variation in unobserved characteristics.

Males and females tend to have similar degrees of selectivity as well as variation in marriagebility. Simulation results indicate that the factors to which selective mating is responsive are preferences and inequality in wages. Changes in the gender wage gap, the level of wages, and residual inequality have trivial effects on selective mating. Nonetheless, older cohorts are more responsive than younger ones to changes in levels of wages and education, as well as to equalization of gender mean wage gaps and wage inequality. People from different geographical locations have similar responses to changes in inequality.

The findings in this study cast important policy implications. Policies that aim at influencing school attendance behavior (e.g. subsidization of school tuition) or wage inequality may have important effects on marriage sorting, which could impact inequality and fertility behavior.

The bottom line is, Darwin's claim about greater female choosiness is not supported, while his assertions of greater male variation and a positive relation between marriage hazard and marriageability (and wages) are supported. These conclusions suggest that Fisher's fears of an endless arms race between male ornamentation and female choosiness may not be reasonable, at least for humans. Insofar as who matches with whom has a nontrivial impact on labor supply, fertility, and mortality, a direction for future research would be to offer the fundamentals for selective sorting.

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Appendix

Equilibrium matching sets are endogenously determined in the model. Given a vector of parameter values, a matching algorithm is proposed to compute the acceptable pool of partners for each type of individual for the matching model. The difficulty in solving for the reservation type and the highest attainable type for each type of individual involves constantly updating the acceptance criteria from other individuals. The acceptable pool of partners can be identified by solving the equilibrium acceptance set backward, starting from the highest type from each gender side.

The Matching Algorithm

Step 1 For the highest type of men and women, set the maximum-attainable type to J.

Step 2 Use equations (3) and (4) to solve for R for the highest type of men and women respectively. $\{R_{i=J}, M_{i=J}\} \times \{R_{j=J}, M_{j=J}\}$ defines the first acceptance area.

Step 3 For any $i-th$ type individuals, where $i < J$, two cases can occur:

Case 1. M_i is identifiable. This occurs when $\{j|R_j <= x_i\}$ is not empty for some $j > j'$. In this case, i is accepted by some $j > j'$. We set $M_i = \max\limits_{j>j'} \{j|R_j <= x_i\}$ and solve for R_i. Repeat for the women's side.

Case 2. M_i is unidentifiable. This occurs when $\{j|R_j <= x_i\}$ is empty for a $j > j'$. In this case, we reverse the role of i and j and solve for $\{R_j, M_j\}$ aiming at determining the acceptance sets of additional $j = j-1, j-2, ...$, until the first woman accepts the $i-th$ man, i.e., $R_j <= x_i$. However, to solve for $\{R_j, M_j\}$, we need to be able to determine $M_j = \max\limits_{i>i'} \{i|R_i <= x_j\}$, which may not be possible if the set is empty. If we hit an empty set of $\{i|R_i <= x_j\}$ before obtaining $R_j <= x_i$, reset M_j to x_i and M_i to x_j at the point of failure and repeat step 3 again.

Stopping Criterion: We have solved for all acceptable sets of partners for type i and j. If there are remaining types of i or j that have not been matched, they will be assigned a null acceptance area (no matching possible.)