Marriage and Employment Returns to Education

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Abstract

How to measure the return to education in the marriage market and compare it to its return in the job market? To achieve this, we develop a method based on a frictionless matching model with transferable utility in the job market and imperfectly transferable utility in the marriage market. Our approach relies on observed match types in each market (spouse and occupation) and incorporates transfer in the job market (earnings) as an additional moment for estimation. Evidence from the U.S. suggests that, for women, marrying a more educated spouse consistently yields positive marriage returns, but this is not always the case for men. Over time, however, there has been a shift, with increased acceptance of graduate-educated wives after 2000. At the lower end of the educational distribution, additional education improves spouse quality more than job quality, whereas at the upper end, the job return significantly surpasses the spouse return. In 2017, women with a bachelor's degree were indifferent between marrying a man with at least a bachelor's degree and a 16 percent increase in earnings (≈\$9,600 in 2023 terms) while remaining single. For men, the corresponding figure was a 20 percent increase in earnings (≈\$19,200 in 2023 terms).

JEL classifications: I26, J12, J16

Keywords: matching, imperfectly transferable utility, marriage market, return to education

1 Introduction

Over the past century, education has expanded dramatically across the globe, with women surpassing men in higher education attainment in many countries (Becker, Hubbard, and Murphy, 2010; Goldin, Katz, and Kuziemko, 2006). Acquiring education results in changing one's prospects in two markets: the labor market and the marriage market. While at the extensive margin, more schooling affects the gain from matching compared to remaining unmatched in the markets (employment vs. non-employment and marriage vs. singlehood), at the intensive margin, it influences the match quality (occupation and spouse

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types), and transfer (earnings and marital surplus share). A key question in this regard is how large the returns to education in each market are and how to compare them. This paper contributes to answering this question methodologically and empirically.

Measuring return to education in the marriage market and comparing it with the return in the labor market is not straightforward. The main difficulty stems from the fact that, unlike the labor market, the transfers in the marriage market are not observable. Therefore, while the labor return can be directly estimated from the observed wage premiums, the marriage return must be indirectly estimated from the observable match qualities and marriage patterns. An important challenge in measuring the return without observing the surplus share of agents arises from the secular changes in population supplies over time or across space. For instance, if the population of highly educated women increases but not that of men, the matching patterns by education will change. However, such changes can occur even under random matching, and it is necessary to differentiate between two components: the mechanical effect resulting from changes in the overall distribution of education levels and the effect caused by changes in the marriage return to education that reflects the benefits of marriage based on education levels.

In this paper, we present a new approach for estimation and comparison of the marriage and employment returns to education, using a frictionless matching model. Our method focuses on the match qualities in both markets instead of the transfer, which is unobservable in the marriage market, and incorporates earnings data from the labor market as additional information for estimation of parameters. The proposed method has several attractive features: first, it jointly estimates different margins of the marriage and employment returns to education and enables comparison between them. Second, the signs of the returns and their differences can be estimated nonparametrically, allowing for partial identification with no specific assumption for the distribution of unobservable terms. Third, the estimated preference parameters enable us to estimate the returns in the marriage market in equivalent dollar terms.

The model extends the seminal work of Choo and Siow (2006) (hereafter CS) on the marriage market into a two bilateral markets matching framework where both genders compete for jobs in the labor market, while competition in the marriage market occurs within each gender to match with the opposite gender. Matching gains in the job market are fully transferable, whereas the marriage market follows an imperfectly transferable utility framework, as in Galichon, Kominers, and Weber (2019) (hereafter GKW). The two markets are interdependent, with the Pareto frontier in the marriage market shaped by household income, which in turn depends on the couple's transfers from the job market.

This model provides a structural approach for measuring the returns to education in both marriage and labor markets, conditional on marital and occupational statuses. These conditional returns are independent of the marginal distributions of education, marriage, and employment, and are partially identified using the contingency table of observed matching frequencies across marriage and job markets. Assuming a Gumbel distribution for the unobserved components, these conditional returns can be aggregated to derive unconditional returns in a straightforward manner.

Using cross-sectional household data from the United States, we estimate the trends in both the extensive and intensive margins of marriage and employment returns to education, along with their differences. Our findings indicate that, for women, marrying up (i.e., with a more educated spouse) consistently yields positive marriage returns, whereas for men, this is not always the case. Notably, until 2000, men with a bachelor's degree or lower did not prefer marrying a graduate-degree woman over a bachelor's-degree woman.

A comparison of the extensive margin indices for marriage and employment returns suggests that, for the transition from some college to a bachelor's degree, employment returns consistently exceed marriage returns for men. In contrast, for women, the marriage returns is higher. However, graduate education enhances employment prospects for both genders, while its relative marriage return for women is negative.

Analyzing the intensive margin returns reveals a monotonic relationship between education and match quality, whereby higher education levels are associated with both higher-quality spouses and better jobs. However, the patterns suggest that education has an increasing and concave relationship with spouse quality, whereas its relationship with job quality is increasing and convex.

The estimated preference parameters in the overidentified model allow for evaluating the value of spouse education for employed individuals. The numbers suggest that, in 2017, relative to high school dropout women, women with bachelor's degrees would pay around 16 percent of their annual earnings (≈$9,600 in 2023) to marry husbands with bachelor's or graduate degrees rather than remaining single. Conversely, they would pay about 13 percent of their annual earnings to avoid marrying a high school dropout man. The corresponding numbers for men with bachelor's degrees are approximately $19,200 to marry a wife with the same educational background instead of remaining single and about $14,700 to avoid marrying a high school dropout wife. This gender disparity in spouse valuation can help explain the rise of female higher education in the U.S., which has surpassed that of men in recent decades (Goldin et al., 2006).

This paper contributes to the literature on multiple fronts. First, it develops a framework for both parametric and nonparametric estimation of the extensive and intensive margins of marriage and employment returns to female education, along with their comparison. In this regard, it aligns with Chiappori, Salanié, and Weiss (2017), who estimate the marriage college premium using a static frictionless matching model.

Among studies integrating marriage and labor market decisions, to our knowledge, only Calvo, Lindenlaub, and Reynoso (2024) explicitly frame these markets as interconnected, similar to this paper. However, their focus is on sorting across the two markets through home production complementarities rather than measuring returns. Additionally, their framework like other models of marriage and labor supply (see Chiappori, Dias, and Meghir, 2018; Blundell, Costa Dias, Meghir, and Shaw, 2016; Goussé, Jacquemet, and Robin, 2017; Gayle and Shephard, 2019, among others) impose parametric restrictions that, while useful for analyzing policy interventions, limit their applicability for measuring and comparing marriage and job market returns to education.[1] This paper offers a nonparametric approach to measuring returns to education by estimating systematic matching surplus using data from a large market, which is preferable to measurements mediated by particular modeling assumptions. A further advantage of this framework is its reliance on cross-sectional data, which are widely available across countries and provide greater statistical power in estimation compared to typical panel datasets.

Next, this paper contributes to the literature on the econometrics of frictionless matching markets. The seminal work of CS builds on a transferable utility model to estimate marriage surplus based on observable traits of married couples and singles. Their key identifying assumption is that the stochastic component is *separable*, meaning it can be decomposed into male and female parts that depend only on the observable traits of their spouse. GKW extend this framework to a setting with imperfectly transferable utility. This paper develops a matching model that integrates two bilateral markets, treating the job market as in CS while modeling the marriage market as in GKW. To the best of our knowledge, this is a novel contribution to this literature, providing a structural foundation for using conditional odds ratios as a measure of association that remains independent of the marginal distribution of the population.

In another direction, the basic CS model, which is just-identified with homoskedastic Gumbel distribution for unobserved heterogeneity, is extended in various ways in the later contributions. Chiappori et al. (2017) employ a multi-market framework, Galichon and Salanie (2021) assume a parametric surplus, and Chiappori et al. (2018) utilize information from later decisions on saving and labor supply to generate additional moments for their empirical estimation. This paper contributes to this literature by exploiting information on earnings across occupations as overidentifying restrictions for discrete choices of individuals. This is a new extension of CS that this paper presents with a great application in disentangling the two different returns to education.

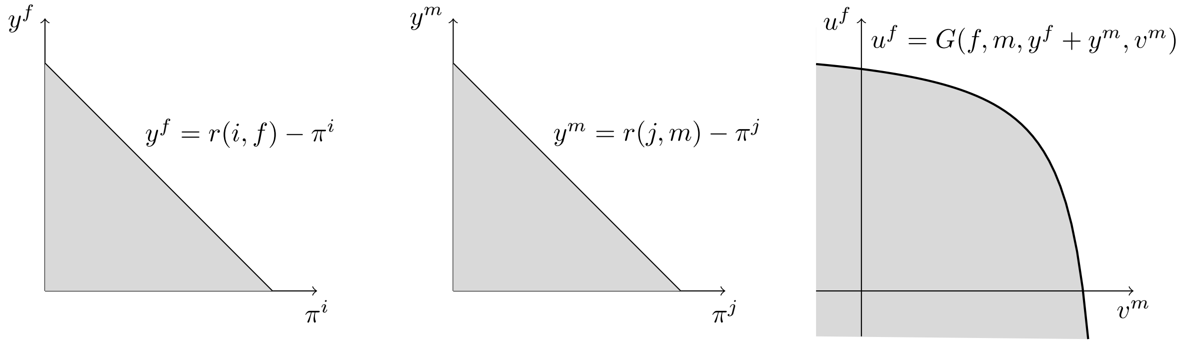
Before proceeding, some remarks are in order. Usually, the term *labor* return refers to the wage premium, but in this paper, we use the term *employment* return because the measurement is based on the discrete choices for employment and job status and not specifically the wage. In addition, we should emphasize that our analysis has a descriptive nature rather than identifying causal relationships.

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework and Section 3 explains identification of the parameters and estimation strategy. Section 4 describes the data and Sections 5 present empirical findings for estimated returns in the United States. Section 6 concludes.

2 Theoretical framework

Our primary objective is to estimate and compare the two returns to education that an individual expects to obtain. To achieve this, we focus on the allocation of agents with specific types across both the job and marriage markets and adopt a static matching model that incorporates equilibrium decisions in

[1] For example, Chiappori et al. (2018) assume that marriage decisions are made before labor supply decisions, with marriage surplus driven solely by monetary benefits from future behavior, excluding its non-pecuniary components.



(a) Job market: women (b) Job market: men (c) Marriage market

Figure 1: Shape of the Pareto set in the matching markets.

these two markets simultaneously. The theoretical framework extends CS to include joint decisions in two bilateral matching markets under a frictionless setting. This approach allows us to determine how much individuals of different types match with particular types of jobs and spouses.

This section outlines our matching model and specifies the separability assumption that links it to the discrete choices of individuals. We then introduce conditional return indices and show how the separability assumption allows for their sign-based identification. Next, we quantify the conditional returns by assuming a Gumbel distribution for unobservable terms. Finally, we address the aggregation of the return indices to derive overall measures of the returns to education.

2.1 Two bilateral matching markets

Suppose there are two bilateral matching markets for jobs and marriages in which the agents play frictionless matching games. In the job market, individuals of both genders compete to match with firms (or jobs). In the marriage market, individuals of the same gender compete to match with members of the opposite gender. In both markets, each individual either remains unmatched or forms a match with an agent from the opposite side of the market.

The environment consists of a large number of players belonging to finite sets $\mathcal{F}, \mathcal{M}$, and $\mathcal{J}$ of women, men, and firms, respectively. In the job market, payoffs are perfectly transferable: a matching between an employee $e \in \mathcal{F}$ and a firm $i \in \mathcal{J}$ generates an output $r(e,i)$, which is divided between the firm and the worker as profit π^i and earnings y^e, respectively. Thus, the feasibility constraint for payoffs in the job market is given by

$$y^f + \pi^i \leq r(f,i), \qquad y^m + \pi^j \leq r(m,j) \tag{1}$$

Figure 1 (a)-(b), show the Pareto frontiers corresponding to the job market matchings for the two genders which are stright lines with slope -1.

In contrast, utility in the marriage market is imperfectly transferable. When a woman f and a man m decide to match, their pair of utilities (u^f, v^m) is constrained by a nonlinear Pareto frontier, as illustrated in Figure 1 (c). Suppose the feasibility constraint in the marriage market is given by

$$u^f \leq G(f,\, m,\, y^f + y^m,\, v^m) \tag{2}$$

The dependency of the Pareto frontier in the marriage market on the sum of the couple's transfers from the job market, $y^f + y^m$, establishes the connection between the two matching markets. This relationship highlights that household consumption in the marriage market originates from earnings in the job market. Single individuals consume only their own income and married couples jointly consume the sum of their earnings.

A simple parametric form for imperfectly transferable utility is

$$u^f = a^{fm} + \ln c^f, \qquad v^m = b^{fm} + \ln c^m, \qquad c^f + c^m = y^f + y^m \tag{3}$$

where a^{fm} and b^{fm} represent the non-transferable components of utilities when f and m decide to match, while c^f and c^m denote their private consumptions. In this framework, utility transfer is imperfectly possible through private consumption, and the resulting Pareto frontier is given by

$$G(f,\, m,\, y^f + y^m,\, v^m) = a^{fm} + \ln\left(y^f + y^m - \exp(v^m - b^{fm})\right)$$

A "matching" is represented by three binary measures $\mu(f,m)$, $\nu(f,i)$, and $\nu'(m,j)$, which take the value 1 if the respective pairs are matched and 0 otherwise. $\mu(f,m)$ represents the matching of Mrs. f and Mr. m in the marriage market, $\nu'(f,i)$ represents the matching of female worker f with firm i in the job market, and $\nu'(m,j)$ represents the matching of male worker m with firm j in the job market. The conditions that individuals either match with a partner or remain unmatched are given by

$$\sum_{m\in\mathcal{M}} \mu(f,m) \leq 1, \quad \sum_{f\in\mathcal{F}} \mu(f,m) \leq 1, \quad \sum_{i\in\mathcal{J}} \nu(f,i) \leq 1, \quad \sum_{j\in\mathcal{J}} \nu'(m,j) \leq 1$$

Since our focus is not on firms, we assume that all jobs are matched with a worker.

$$\sum_{f\in\mathcal{F}} \sum_{m\in\mathcal{M}} \nu(f,i) + \nu'(m,i) = 1$$

Appendix Figure A.1 illustrates a simple matching table with four individuals and four jobs.

In this framework, μ, ν and ν' determine who matches with whom, but the gains from matching and the stability condition depend on the payoffs of the agents. A matching is *stable* in a market if

(i) In all matched pairs, both players prefer being matched together over being matched with others,

(ii) No matched player would prefer to remain unmatched.

To formalize the stability conditions, we must define the payoffs for agents in cases of non-employment and remaining single. In the job market, the payoff of non-employment for worker e is simply $y^e = 0$. In the marriage market, we assume the functions $G_0(f, y^f)$ and $G_0(m, y^m)$ determine the utilities of Miss f and Mr m when they remain single and earn y^f and y^m from the job market, respectively. The function $G_0(e, y^e)$ is assumed to be increasing in earnings y^e.

In the job market, stability conditions in terms of payoff functions are

$$\forall\, e, i \in \mathcal{F} \cup \mathcal{M}\,, i \in \mathcal{J} \begin{cases} y^e + \pi^i \geq r(e\,, i) & (4) \\ y^e \geq 0,\;\; \pi^i \geq 0 & (5) \end{cases}$$

Conditions (4) and (5) correspond to stability criteria (i) and (ii), respectively. If any of these conditions do not hold, for example if $y^e + \pi^j < r(e, j)$, then both e and j strictly prefer matching with each other over their current status because they can share the extra surplus. Similarly, if $y^e < 0$, the individual e would prefer not to work. In the marriage market, the stability conditions require

$$\forall\; f \in \mathcal{F},\;\; m \in \mathcal{M} \begin{cases} u^f \geq G(f,\, m,\, y^f + y^m,\, v^m) & (6) \\ u^f \geq G_0(f,\, y^f) & (7) \\ v^m \geq G_0(m,\, y^m) & (8) \end{cases}$$

Here (6) corresponds to condition (i) and (7)-(8) correspond to condition (ii). By combining (4)-(8), the stability conditions across both markets, based on the payoffs of agents, are expressed as follows

$$\forall\; f \in \mathcal{F},\;\; m \in \mathcal{M},\;\; i, j \in \mathcal{J},\;\; i \neq j \begin{cases} u^f \geq G\big(f,\, m,\, r(f, i) + r(m, j) - \pi^i - \pi^j,\, v^m\big) \\ u^f \geq G_0\big(f,\, r(f, i) - \pi^i\big), \quad v^m \geq G_0\big(m,\, r(m, j) - \pi^j\big) \\ \pi^i \geq 0, \quad r(f,\, i) - \pi^i \geq 0 \\ \pi^j \geq 0, \quad r(m,\, j) - \pi^j \geq 0 \end{cases} \tag{9}$$

If any of these conditions does not hold for an unmatched group of agents, it becomes desirable for them to leave their current partners, match together, and share the extra surplus.

The stability conditions (9), combined with the feasibility conditions (1) and (2), imply that, at a *stable matching equilibrium*, the relationships summarized in Table 1 hold, based on the matching status of the agents.

2.2 Separable structure for unobservables

Suppose the population consists of a large number of men, women, and jobs, categorized into a small number of types that are observable to the researcher. Since our focus is on the two returns to education, we classify men and women by their education levels into N_E groups and categorize jobs into N_J groups based on their skill requirements. Without loss of generality, we assume that the education and job classifications are symmetric across genders.

Table 1: Relationship between the payoffs at the stable matching.

matching assignment			relationship between payoffs
$\mu(f,m)=1$	$\nu(f,i)=1$	$\nu'(m,j)=1$	$u^f = G\big(f,\, m,\, r(f,i)+r(m,j)-\pi^i-\pi^j,\, v^m\big)$
$\mu(f,m)=1$	$\nu(f,i)=1$	$\sum_j \nu'=0$	$u^f = G\big(f,\, m,\, r(f,i)-\pi^i,\, v^m\big)$
$\mu(f,m)=1$	$\sum_i \nu=0$	$\nu'(m,j)=1$	$u^f = G\big(f,\, m,\, r(m,j)-\pi^j,\, v^m\big)$
$\mu(f,m)=1$	$\sum_i \nu=0$	$\sum_j \nu'=0$	$u^f = G\big(f,\, m,\, 0,\, v^m\big)$
$\sum_m \mu=\sum_f \mu=0$	$\nu(f,i)=1$	$\nu'(m,j)=1$	$u^f = G_0\big(f, r(f,i)-\pi^i\big),\ v^m = G_0\big(m, r(m,j)-\pi^j\big)$
$\sum_m \mu=\sum_f \mu=0$	$\nu(f,i)=1$	$\sum_j \nu'=0$	$u^f = G_0\big(f, r(f,i)-\pi^i\big),\ v^m = G_0\big(m,0\big)$
$\sum_m \mu=\sum_f \mu=0$	$\sum_i \nu=0$	$\nu'(m,j)=1$	$u^f = G_0\big(f,0\big),\quad v^m = G_0\big(m, r(m,j)-\pi^j\big)$
$\sum_m \mu=\sum_f \mu=0$	$\sum_i \nu=0$	$\sum_j \nu'=0$	$u^f = G_0\big(f,0\big),\quad v^m = G_0\big(m,0\big)$

We rank both education groups and job classifications in ascending order, with the lowest class ranked as 1 and the highest classes as N_E and N_J, respectively. Let $F \in \{1,\dots,N_E\}$ denote women's education categories, $M \in \{1,\dots,N_E\}$ denote men's education categories, $I \in \{0,1,\dots,N_J\}$ denote women's employment classifications, and $J \in \{0,1,\dots,N_J\}$ denote men's employment classifications. Here, $I=0$ and $J=0$ represent non-working women and men, respectively, while $I,J \geq 1$ correspond to different occupations.

The classification of spouses corresponds to their education and job classifications. In this regard, husband and wife categories are defined by MJ and FI, respectively, such that $M,F \in \{1,\dots,N_E\}$ and $I,J \in \{0,\dots,N_J\}$. Similar to employment classifications, we let $MJ=00$ and $FI=00$ represent fictitious spouse categories for single women and men, respectively.[2]

The purpose of categorizing the population is to decompose an agent's gains from matching in each market into a deterministic component, determined by observable types, and a random component, which reflects unobserved heterogeneity in traits and preferences. We denote the categories by capital letters in the subscript and individual indices by lowercase letters in the superscript. If we focus solely on matching in the job market, since the payoffs are perfectly transferable, we can define the matching surplus $r(e\in E, j\in J)$ and express it as:

$$r(e\in E, j\in J) = R_{EJ} + \varepsilon^{ej} \tag{10}$$

Starting from CS, a central assumption in frictionless matching models with *transferable utility* is the additive separability of the unobservable terms with respect to the categories. In equation (10), this implies $\varepsilon^{ej} = \eta^e_J + \gamma^j_E$, where η^e_J and γ^j_E are independent random variables. From a technical perspective, separability eliminates interactions between partners' unobserved heterogeneity in determining the total gains from matching. The key advantage of this assumption is that it simplifies the complexity of a two-sided matching problem by reducing it to a series of one-sided problems.[3]

Under the separability assumption $\varepsilon^{ej} = \eta^e_J + \gamma^j_E$, if worker $e\in E$ matches with job $j\in J$ in a stable

[2] In this notation, $F=0$ means $I=0$ and $M=0$ means $J=0$.

[3] See Galichon and Salanie (2021) for further technical details and Chiappori (2017, pp. 89-91) for justifications of the separability assumption.

matching, we have:[4]

$$y^e_J = Y_{EJ} + \eta^e_J, \qquad \pi^j_E = \Pi_{EJ} + \gamma^j_E$$

This implies that with separable unobservables, a firm's profit and a worker's earnings depend only on the categories of their matched partners, not on their specific individual characteristics. In this framework, η^e_J captures both worker e's preferences for job category J and the qualities of e that are particularly attractive or unattractive for that category. Similarly, γ^j_E reflects the specific appeal of job j for workers in category E and vice versa. Therefore, while separability allows for matching on unobservables, it rules out sorting based on only the unobserved characteristics on both sides of the market.

GKW extend the separability of unobservable components in bilateral matching models with *imperfectly transferable* utility by assuming that the shape of Pareto frontier is determined only by agents' categories, not on their individual characteristics. In a market with Pareto frontier $u^f = G(f, m, v^m)$, GKW's separability assumption is $u^f - \alpha^f_M = G(F, M, v^m - \beta^m_F)$. In our framework, the Pareto frontier additionally depends on individuals' payoffs from the job market, requiring the consideration of separability across both markets.

Assumption 1 (Separability in both markets)**.** *If $f \in F$ with job $i \in I$ is matched with $m \in M$ with job $j \in J$, then their Pareto frontier in the marriage market is separable as*

$$u^f - \alpha^f_{IMJ} = G(F,\, M,\, R_{FIMJ} - \pi^i + \gamma^i_{FMJ} + R'_{FIMJ} - \pi^j + \gamma^j_{FIM},\, v^m - \beta^m_{FIJ})$$

For single individuals $u^f - \alpha^f_{I00} = G_0(F,\, R_{FI00} - \pi^i + \gamma^i_{F00})$, $v^m - \beta^m_{J00} = G_0(M,\, R'_{MJ00} - \pi^j + \gamma^j_{M00})$, where all $\alpha^f_{IMJ}, \beta^m_{FIJ}, \gamma^i_{FMJ}, \gamma^j_{FIM}$ are independent random variables.

Using this assumption, we can decompose agents' payoffs from both markets into deterministic and stochastic components.

Proposition 1. *Under Assumptions 1, there exist numbers $U_{FIMJ}, V_{FIMJ}, \Pi_{FIMJ}$, and Π'_{FIMJ}, for all possible values of F, M, I, J, such that at the stable matching, if woman $f \in F$ matches with job $i \in J$ and a husband, who is a man $m \in M$ with job $j \in J$, the payoffs are:*

$$u^f_{IMJ} = U_{FIMJ} + \alpha^f_{IMJ}, \quad v^m_{FIJ} = V_{FIMJ} + \beta^m_{FIJ}, \quad \pi^i_{FMJ} = \Pi_{FIMJ} + \gamma^i_{FMJ}, \quad \pi^j_{FIM} = \Pi'_{FIMJ} + \gamma^j_{FIM}$$

and the deterministic utilities are linked as follows:

$$U_{FI00} = G_0(F,\, Y_{FI00}), \quad V_{00MJ} = G_0(M,\, Y_{00MJ}), \quad \forall H, W \neq 0:\; U_{FIH} = G(F,\, M,\, Y_{FIMJ},\, V_{FIMJ}),$$

where $Y_{FI00} = R_{FI00} - \Pi_{FI00}$, $Y_{00MJ} = R'_{00MJ} - \Pi'_{00MJ}$, and $Y_{FIMJ} = R_{FIMJ} - \Pi_{FIMJ} + R'_{FIMJ} - \Pi'_{FIMJ}$.

[4] see Chiappori et al. (2017, Proposition 1)

With a distributional assumption on the unobserved terms, the deterministic payoffs can be recovered from observed matching patterns (Galichon and Salanie, 2021). Without imposing parametric assumptions on U_{FIMJ} and V_{FIMJ}, we assume that α^f_{IMJ} and β^m_{FIJ} have zero mean within their respective categories F and M. Subsequently, the deterministic utilities U_{FIMJ} and V_{FIMJ} can be used to compute the returns for women and men, respectively. In the rest of this section, we focus the analysis and define indices on women, but all applies to men as well.

2.3 Conditional returns and sign-based identification

We begin by defining the conditional returns and their differences, which serve as the foundation for measuring aggregate indices. For a woman with education level F, the deterministic surplus of marriage $MJ \neq 00$ conditional on employment status I is $U_{FIMJ} - U_{FI00}$. Therefore, conditional on the husband's type MJ and employment status I, we can define the marriage return to attaining education F_2 compared to F_1 as the difference in their marriage surplus

$$r^m_{F_1F_2IMJ} = U_{F_2IMJ} - U_{F_2I00} - (U_{F_1IMJ} - U_{F_1I00}), \qquad MJ \neq 00 \tag{11}$$

Similarly, we define the conditional employment return to education F_2 compared to F_1 as

$$r^e_{F_1F_2IMJ} = U_{F_2IMJ} - U_{F_20MJ} - (U_{F_1IMJ} - U_{F_10MJ}), \qquad I \neq 0 \tag{12}$$

In this framework, the joint marriage and employment return to education F_2 compared to F_1 conditional on marriage MJ and employment I is

$$r^{me}_{F_1F_2IMJ} = U_{F_2IMJ} - U_{F_200} - (U_{F_1IMJ} - U_{F_100}), \qquad I \neq 0, MJ \neq 00 \tag{13}$$

and the conditional difference between marriage MJ and employment I returns to education level F_2 compared to education level F_1 becomes

$$\delta^{me}_{F_1F_2IMJ} = U_{F_20MJ} - U_{F_10MJ} - (U_{F_2I0} - U_{F_1I0}) \quad I \neq 0, MJ \neq 00 \tag{14}$$

The first difference in (14) is the surplus of higher education for a non-working woman married to husband MJ, and the second difference is the surplus of higher education for a single woman employed as I. Therefore, conditional on spouse MJ and job I, the difference between marriage and employment returns to female education is equal to the difference in the higher education surplus of married non-working women and single working women.

Next, we link between the return indices and the empirical matching patterns. For this purpose, we build population contingency tables that characterizes the number of individuals in different combinations of education, occupation, and marriage categories. For women, such a table has three dimensions $N_F \times (1 + N_J) \times (1 + N_F \times N_J)$ and its element corresponding to row F, column I, and layer MJ, is the population of women with education F, job I, and husband MJ. In the rest of analysis, we use $\langle ., ., ., . \rangle$ with below notations to show different subsets of population:

- $\langle F, I, M, J \rangle$: women with education F, job I, and husband MJ
- $\langle F, I, +, + \rangle$: women with education F and job I
- $\langle F, I, \geq 1, + \rangle$: women with education F, job I, and married (husband $MJ \neq 00$)
- $\langle F, I, M, + \rangle$: women with education F, job I, and a husband with education M

Similar subsets can be applied for jobs (e.g. $\langle F, +, M, J \rangle$, $\langle F, \geq 1, M, J \rangle$), and men (e.g. $\langle F, I, M, J \rangle$, $\langle +, +, M, J \rangle$, $\langle \geq 1, +, M, J \rangle$, $\langle F, +, M, J \rangle$).

The following proposition shows how we can identify the signs of the conditional return indices and their differences, using the empirical matching frequencies.

Proposition 2. *If α^f_{IMJ} is i.i.d. and its distribution function $F_\alpha(\cdot)$ is strictly increasing with bounded and continuous derivatives, then at the stable matching*

$$
\begin{aligned}
r^m_{F_1F_2IMJ} \gtreqless 0 \;&\Leftrightarrow\; \ln \frac{\langle F_2, I, M, J \rangle \langle F_1, I, 0, 0 \rangle}{\langle F_2, I, 0, 0 \rangle \langle F_1, I, M, J \rangle} \gtreqless 0 \\
r^e_{F_1F_2IMJ} \gtreqless 0 \;&\Leftrightarrow\; \ln \frac{\langle F_2, I, M, J \rangle \langle F_1, 0, M, J \rangle}{\langle F_2, 0, M, J \rangle \langle F_1, I, M, J \rangle} \gtreqless 0 \\
r^{me}_{F_1F_2IMJ} \gtreqless 0 \;&\Leftrightarrow\; \ln \frac{\langle F_2, I, M, J \rangle \langle F_1, 0, 0, 0 \rangle}{\langle F_2, 0, 0, 0 \rangle \langle F_1, I, M, J \rangle} \gtreqless 0 \\
\delta^{me}_{F_1F_2IMJ} \gtreqless 0 \;&\Leftrightarrow\; \ln \frac{\langle F_2, 0, M, J \rangle \langle F_1, I, 0, 0 \rangle}{\langle F_2, I, 0, 0 \rangle \langle F_1, 0, M, J \rangle} \gtreqless 0
\end{aligned}
$$

This proposition generalizes an attractive property of the separable models of frictionless marriage markets. Graham (2011) shows that in a one-to-one matching framework under separability and i.i.d. feature for the unobservables, the sign of the local degree of complementarity is identified. Proposition 2 shows that this sign-based identification is valid for the conditional returns indices, which have a form of local complementarity in a two bilateral matching framework. This remarkable property of the model asserts that based on the matching patterns and with no further parametric assumption, we can determine not only the signs of the conditional marriage and employment returns to education at different margins but also which one is bigger than the other.

2.4 Extreme value distribution and the conditional returns

Following the previous literature, we assume that the unobservables terms have Gumbel (type-I extreme value) distribution. This assumption gives a closed-form formula for conditional choice probabilities.[5]

[5]In section 3, we partly relax this assumption by utilizing earnings data and adding heteroskedasticity in unobservable for estimations.

Proposition 3. *If α^f_{IMJ} has Gumbel distribution, i.e., $CDF_\alpha(x) = e^{-e^{-x}}$,*

$$r^m_{F_1F_2IMJ} = \ln \frac{\langle F_2, I, M, J\rangle\langle F_1, I, 0, 0\rangle}{\langle F_2, I, 0, 0\rangle\langle F_1, I, M, J\rangle} \tag{15}$$

$$r^e_{F_1F_2IMJ} = \ln \frac{\langle F_2, I, M, J\rangle\langle F_1, 0, M, J\rangle}{\langle F_2, 0, M, J\rangle\langle F_1, I, M, J\rangle} \tag{16}$$

$$r^{me}_{F_1F_2IMJ} = \ln \frac{\langle F_2, I, M, J\rangle\langle F_1, 0, 0, 0\rangle}{\langle F_2, 0, 0, 0\rangle\langle F_1, I, M, J\rangle} \tag{17}$$

$$\delta^{me}_{F_1F_2IMJ} = \ln \frac{\langle F_2, 0, M, J\rangle\langle F_1, I, 0, 0\rangle}{\langle F_2, I, 0, 0\rangle\langle F_1, 0, M, J\rangle} \tag{18}$$

The right-hand sides of (15) and (17) have similar units as conditional log odds ratios incorporating the relative importance of success/failure probabilities in terms of their level of magnitude. Notably, the conditional odds ratio does not depend on the marginal distributions of the discrete variables.[6] This property is important in our analysis because the marginal distributions of education, employment, and marriage may significantly change across space and time. For measuring returns to female education in a specific time and location, we need a method that separates the interaction of female education with marriage and employment from the prevalence of female education, marriage, and employment, per se. The difference in prevalence can stem from factors out of the focus of analysis, such as the cost of education, the structure of labor demand, and marriage norms. With the same logic, Siow (2015) and Chiappori, Costa Dias, and Meghir (2021) use the log odds ratio as an index of marriage assortativeness that measures changes in sorting and not changes in the marginal distributions of education for men and women. Also, Long and Ferrie (2013) use odds ratio to measure intergenerational occupational mobility irrespective of marginal distributions of occupation across two generations.

2.5 Aggregating conditional returns to education

So far, our analysis of the return indices was conditional on I and MJ. The below Proposition show how we can aggregate conditional deterministic utilities when the unobservable terms have Gumbel distribution.

Proposition 4. *If α^f_{IMJ} has standard Gumbel distribution, Υ is the Euler's constant, and $U_{F000} = 0$:*

$$\bar{U}_{F,\mathcal{I},\mathcal{M}\mathcal{J}} := E[\max_{f\in F} u^f_{IMJ} \mid I \in \mathcal{I}, M \in \mathcal{M}, J \in \mathcal{J}] - \Upsilon = \ln \sum_{\substack{I\in\mathcal{I}\\ M\in\mathcal{M}\\ J\in\mathcal{J}}} e^{U_{FIMJ}} = \ln \frac{\langle F, I \in \mathcal{I}, M \in \mathcal{M}, J \in \mathcal{J}\rangle}{\langle F, 0, 0, 0\rangle}$$

Here, $\bar{U}_{F,\mathcal{I},\mathcal{M},\mathcal{J}}$ is the expected utility of a woman f when restricted to match with a job and a husband in classification sets $\mathcal{I}, \mathcal{M}$ and $\mathcal{J}$, respectively. Using this feature of Gumbel distribution, we can aggregate utilities and find unconditional returns. In this regard, we define two aggregate marriage

[6]If we re-weight each dimension by fixed vectors a^F, b^I, and c^H, the conditional odds ratios do not change.

returns of increase in education from F_1 to F_2 as

$$r^m_{F_1F_2M} = \bar{U}_{F_2,+,M,+} - \bar{U}_{F_2,+,0,0} - \bar{U}_{F_1,+,M,+} + \bar{U}_{F_1,+,0,0} = \ln \frac{\langle F_2,+,M,+\rangle\langle F_1,+,0,0\rangle}{\langle F_2,+,0,0\rangle\langle F_1,+,M,+\rangle} \tag{19}$$

$$r^m_{F_1F_2} = \bar{U}_{F_2,+,\geq 1,+} - \bar{U}_{F_2,+,0,0} - \bar{U}_{F_1,+,\geq 1,+} + \bar{U}_{F_1,+,0,0} = \ln \frac{\langle F_2,+,\geq 1,+\rangle\langle F_1,+,0,0\rangle}{\langle F_2,+,0,0\rangle\langle F_1,+,\geq 1,+\rangle} \tag{20}$$

$r^m_{F_1F_2M}$ is the marriage return conditional on a husband with education $1 \leq M \leq N_E$, and $r^m_{F_1F_2}$ is the unconditional marriage return. Similarly, we define two aggregate employment return of increase in education from F_1 to F_2 as

$$r^e_{F_1F_2I} = \bar{U}_{F_2,I,+,+} - \bar{U}_{F_2,0,+,+} - \bar{U}_{F_1,I,+,+} + \bar{U}_{F_1,0,+,+} = \ln \frac{\langle F_2,I,+,+\rangle\langle F_1,0,+,+\rangle}{\langle F_2,0,+,+\rangle\langle F_1,I,+,+\rangle} \tag{21}$$

$$r^e_{F_1F_2} = \bar{U}_{F_2,\geq 1,+,+} - \bar{U}_{F_2,0,+,+} - \bar{U}_{F_1,\geq 1,+,+} + \bar{U}_{F_1,0,+,+} = \ln \frac{\langle F_2,\geq 1,+,+\rangle\langle F_1,0,+,+\rangle}{\langle F_2,0,+,+\rangle\langle F_1,\geq 1,+,+\rangle} \tag{22}$$

where $r^e_{F_1F_2I}$ is the employment return conditional on a job $1 \leq I \leq N_J$, and $r^e_{F_1F_2}$ is the unconditional employment return. Regarding the joint return and the difference between marriage and employment returns to education F_2 compared to F_1, we define the aggregate measure

$$r^{me}_{F_1F_2} = \bar{U}_{F_2,\geq 1,\geq 1,+} - \bar{U}_{F_2,0,0,0} - \bar{U}_{F_1,\geq 1,\geq 1,+} + \bar{U}_{F_1,0,0,0} = \ln \frac{\langle F_2,\geq 1,\geq 1,+\rangle\langle F_1,0,0,0\rangle}{\langle F_2,0,0,0\rangle\langle F_1,\geq 1,\geq 1,+\rangle} \tag{23}$$

$$\delta^{me}_{F_1F_2} = \bar{U}_{F_2,0,\geq 1,+} - \bar{U}_{F_1,0,\geq 1,+} - \bar{U}_{F_2,\geq 1,0,0} + \bar{U}_{F_1,\geq 1,0,0} = \ln \frac{\langle F_2,0,\geq 1,+\rangle\langle F_1,\geq 1,0,0\rangle}{\langle F_2,\geq 1,0,0\rangle\langle F_1,0,\geq 1,+\rangle} \tag{24}$$

The indices defined in (19) to (24) gauge the extensive margins of the returns to education, i.e., how much higher education changes the gain from marriage compared to singlehood, and the gain from working compared to not working. At the intensive margin, education influences the quality of marriage and employment. In contrast to the extensive margins of the returns, in which the order of classifications are not important, for measuring the intensive margins of the returns, we need to measure how much higher education improves or worsens the quality of marriage and employment. In this regard, since education and job classifications are ranked by their indices, we define conditional returns at the intensive margin by comparing utilities with the first category of education and occupation

$$r^s_{F_1F_2M} = \bar{U}_{F_2,+,M,+} - \bar{U}_{F_2,+,1,+} - \bar{U}_{F_1,+,M,+} + \bar{U}_{F_1,+,1,+} = \ln \frac{\langle F_2,+,M,+\rangle\langle F_1,+,1,+\rangle}{\langle F_2,+,1,+\rangle\langle F_1,+,M,+\rangle} \tag{25}$$

$$r^s_{F_1F_2} = U_{F_2,+,\geq 2,+} - U_{F_2,+,1,+} - U_{F_1,+,\geq 2,+} + U_{F_1,+,1,+} = \ln \frac{\langle F_2,+,\geq 2,+\rangle\langle F_1,+,1,+\rangle}{\langle F_2,+,1,+\rangle\langle F_1,+,\geq 2,+\rangle} \tag{26}$$

$$r^j_{F_1F_2I} = U_{F_2,I,+,+} - U_{F_2,1,+,+} - U_{F_1,I,+,+} - U_{F_1,1,+,+} = \ln \frac{\langle F_2,I,+,+\rangle\langle F_1,1,+,+\rangle}{\langle F_2,1,+,+\rangle\langle F_1,I,+,+\rangle} \tag{27}$$

$$r^j_{F_1F_2} = U_{F_2,\geq 2,+,+} - U_{F_2,1,+,+} - U_{F_1,\geq 2,+,+} + U_{F_1,1,+,+} = \ln \frac{\langle F_2,\geq 2,+,+\rangle\langle F_1,1,+,+\rangle}{\langle F_2,1,+,+\rangle\langle F_1,\geq 2,+,+\rangle} \tag{28}$$

Conditional on $M, I \geq 2$, $r^s_{F_1F_2M}$ and $r^j_{F_1F_2I}$ gauge the *better spouse* surplus and the *better job* surplus of higher education compared to their bottom ranked categories, respectively. Similar to (23) and (24), we can define the aggregate joint return and difference between better spouse and better job surpluses of higher education conditional on I and M as

$$r^{sj}_{F_1F_2} = U_{F_2,\geq 2,\geq 2,+} - U_{F_1,1,1,+} - U_{F_2,\geq 2,\geq 2,+} + U_{F_1,1,1,+} = \ln \frac{\langle F_2, \geq 2, \geq 2, +\rangle\langle F_1, 1, 1, +\rangle}{\langle F_2, 1, 1, +\rangle\langle F_1, \geq 2, \geq 2, +\rangle} \tag{29}$$

$$\delta^{sj}_{F_1F_2} = U_{F_2,1,\geq 2,+} - U_{F_1,1,\geq 2,+} - U_{F_2,\geq 2,1,+} + U_{F_1,\geq 2,1,+} = \ln \frac{\langle F_2, 1, \geq 2, +\rangle\langle F_1, \geq 2, 1, +\rangle}{\langle F_2, \geq 2, 1, +\rangle\langle F_1, 1, \geq 2, +\rangle} \tag{30}$$

For conciseness, we use the following terminology to describe the extensive and intensive margins of the returns to education in the rest of the paper:

- *Marriage return* r^m: The extensive margin of the marriage return to education compared to singlehood as in (19) and (20).
- *Employment return* r^e: The extensive margin of the employment return to education compared to not working as in (21) and (22).
- *Spouse return* r^s: The intensive margin of the marriage return to education measuring better spouse surplus as in (25) and (26).
- *Job return* r^j: The intensive margin of the employment return to education measuring better job surplus as in (27) and (28).

Similar to Proposition 2, we can show that even without Gumbel distribution for unobservable terms, as long as they are i.i.d, the sign of the aggregate indices are the same as the sign of their corresponding odds ratio.

3 Empirical methodology

The extreme value assumption for α^f_{IMJ} and β^m_{IMJ} provides straightforward formulas to compute the return indices based on the relevant conditional odds ratios derived from the population contingency table. In other words, using only the population contingency table and no additional data, all the return indices listed in (19) to (30) can be computed. However, relying solely on empirical matching patterns results in a just-identified estimation of the parameters, leaving no room for incorporating additional parameters into the model or conducting statistical inference. In fact, the original CS framework represents a nonparametric estimation of the matching surplus patterns, assuming a fixed structure for the distribution of unobserved heterogeneity.

Previous studies have extended the CS model into an over-identified framework by incorporating multiple markets (Chiappori et al., 2017), introducing parametric surplus functions (Galichon and Salanie, 2021), and using future information of household decisions to recover the marriage surplus (Chiappori et al., 2018). In our model, which integrates labor market decisions alongside the marriage market, we can leverage earnings data as a measure of transfers from the job market to the household. This approach allows us to transform the just-identified structure into an over-identified model, offering a novel contribution to this literature.

3.1 Parametric assumption on Pareto frontier

To specify additional earning moments for estimation, we adopt the ETU framework of GKW, as briefly outlined in Section 2. Specifically, we assume the following form for the deterministic utilities at the stable matching:

$$U_{FIMJ} = A_{FM} + B_{FI} + \tau_{FM} \ln C_{FIMJ} \tag{31}$$

$$V_{FIMJ} = A'_{FM} + B'_{MJ} + \tau_{FM} \ln C'_{FIMJ} \tag{32}$$

where A and A' are the non-economic gains that women and men obtains from specific matching type in the marriage market, B and B' represent non-economic components of their utilities from the type of matching in the job market, C and C' respresent private consumption of women and men, respectively, and $\tau \in [0, +\infty)$ is the transferability coefficient. When $\tau \to 0$, the utility is non-transferable and when $\tau \to +\infty$, the utility is perfectly transferable. This parametric structure enables us to incorporate additional moments from average earnings data into the estimation.

Two assumption is made in (31) and (32). First, τ is the same parameter for both genders in a given couple type FM, because otherwise it is not possible to get a closed-form solution for the Pareto frontier. Second, non-economic components A, B are separable in the job and marriage markets and the preference parameter τ are changing based on only education of partners and not their jobs. The reason for this assumption is identification. As shown in Theorem of GKW identification of transferibility parameter require data on transfer between partners in multiple market in which the parameter is constant. In our approach, multiple jobs for same type of individuals is the trick to identify the transferability parameter. Here, our approach is based on multiple jobs of same type of individuals.

In the above collective model with budget constraint $C_{FIMJ} + C'_{FIMJ} = Y_{FIMJ}$, we have

Proposition 5. *In the collective model characterized by (31) and (32), couple's Pareto Frontier becomes*

$$\begin{aligned} &\exp\big(\frac{U_{FIMJ} - U_{F0M0} - U_{FI00} + U_{F000}}{\tau_{FM}}\big)\, Y_{FI00}^{\frac{\tau_{F0}}{\tau_{FM}}} + \\ &\exp\big(\frac{V_{FIMJ} - V_{F0M0} - V_{00MJ} + V_{00M0}}{\tau_{FM}}\big)\, Y_{00MJ}^{\frac{\tau_{0M}}{\tau_{FM}}} = Y_{FIMJ} \end{aligned} \tag{33}$$

Here, the first and second terms in the left-hand side are C_{FIMJ} and C'_{FIMJ}, respectively.

Note that if one of the spouses in a couple does not work (either Y_{F0MJ} or Y_{FIM0}), we need an assumption for his/her hypothetical income if being single. For those partners, we assume a singlehood income equal to the expected income of working singles of the same gender and education. We denote these reservation incomes by $\hat{Y}_{F000}$ and $\hat{Y}_{00M0}$, and as shown in Appendix A.5, they are equal to

$$\hat{Y}_{F000} = \left(\sum_{I=1}^{N_J} \frac{\langle F,\, I\,, 0\,, 0 \rangle}{\langle F,\, \geq 1, 0\,, 0 \rangle} Y_{FI00}^{-\tau_{F0}} \right)^{\frac{-1}{\tau_{F0}}} \qquad \hat{Y}_{00M0} = \left(\sum_{J=1}^{N_J} \frac{\langle 0,\, 0,\, M,\, J \rangle}{\langle 0, 0, M,\, \geq 1 \rangle} Y_{00MJ}^{-\tau_{0M}} \right)^{\frac{-1}{\tau_{0M}}} \tag{34}$$

In addition to the moment equation (33), under Gumbel distributional assumption for unobservable terms, from the proof of Proposition 3, we have

$$U_{FIMJ} - U_{FI'M'J'} = \ln \frac{\langle F, I\,, M\,, J\,\rangle}{\langle F, I', M', J' \rangle}, \qquad V_{FIMJ} - V_{F'I'MJ'} = \ln \frac{\langle F\,, I\,, M, J\,\rangle}{\langle F', I', M, J' \rangle} \tag{35}$$

The earnings moments of Proposition 5 together with the population moments (35) build an over-identified system to estimate the parameter vector U, V and τ with $N_E^2\big((N_J+1)^2 - 2\big) - 2N_E$ over-identifying restrictions (see Appendix A.6).

3.2 Minimum distance estimator

We estimate the vector of parameters $\theta = (U, V, \tau)$ by a minimum distance estimator as

$$\min \; \lambda^T(\theta) \times \Omega^{-1} \times \lambda(\theta) \tag{36}$$

where $\lambda(\theta)$ is the vector of moment conditions and the weighting matrix Ω^{-1} is the inverse of the variance-covariance matrix of the empirical moments as the optimal weighting based on the theory of the MDE. Appendix A.6 describes the exact specification of $\lambda(\theta)$ and how Ω is computed from data by assuming a multinomial distribution for the matching patterns and diagonal covariance structure for earnings. In the optimal MDE, the variance-covariance matrix of the parameters can be recovered from $\text{Var}(\theta) = (\Lambda^T \times \Omega^{-1} \times \Lambda)^{-1}$ where Λ is the derivative matrix of the vector of moment equations $\lambda(\theta)$ with respect to the vector of structural parameters θ. Finally, after estimation of deterministic utilities U, V, we can aggregate them using Proposition 4 and compute different return indices that introduced in section 2.5.

3.3 Aggregate Economic and Non-economic Returns

From Proposition 4, we can aggregate utilities as follows

$$\bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}} = \ln\left(\sum_{I\in\mathcal{I}}\sum_{M\in\mathcal{M}}\sum_{J\in\mathcal{J}} e^{U_{FIMJ}}\right) = \ln\left(\sum_{I\in\mathcal{I}} e^{U_{FI00}-U_{F000}} Y_{FI00}^{-\tau_{F0}} \sum_{M\in\mathcal{M}} e^{U_{F0M0}} \sum_{J\in\mathcal{J}} C_{FIMJ}^{\tau_{FM}}\right)$$

$$= \bar{U}_{F\mathcal{I}00} + \bar{U}_{F0\mathcal{M}0} - U_{F000} - \tau_{F0}\ln\bar{Y}_{F\mathcal{I}00} + \bar{\tau}_{F\mathcal{M}}\ln\bar{C}_{F\mathcal{I}\mathcal{M}\mathcal{J}} + \sum_{J\in\mathcal{J}} 1$$

where $\bar{U}_{F\mathcal{I}00} = \ln\big(\sum_{I\in\mathcal{I}} e^{U_{FI00}}\big)$, $\quad \bar{U}_{F0\mathcal{M}0} = \ln\big(\sum_{M\in\mathcal{M}} e^{U_{F0M0}}\big)$, $\quad \bar{Y}_{F\mathcal{I}00} = \Big(\frac{\sum_{I\in\mathcal{I}} e^{U_{FI00}} Y_{FI00}^{-\tau_{F0}}}{\sum_{I\in\mathcal{I}} e^{U_{FI00}}}\Big)^{\frac{-1}{\tau_{F0}}}$

$$\bar{C}_{F\mathcal{I}\mathcal{M}\mathcal{J}} = \left(\frac{\sum_{I\in\mathcal{I}} e^{U_{FI00}} Y_{FI00}^{-\tau_{F0}} \sum_{M\in\mathcal{M}} e^{U_{F0M0}} \sum_{J\in\mathcal{J}} C_{FIMJ}^{\tau_{FM}}}{\sum_{I\in\mathcal{I}} e^{U_{FI00}} Y_{FI00}^{-\tau_{F0}} \sum_{M\in\mathcal{M}} e^{U_{F0M0}} \sum_{J\in\mathcal{J}} 1}\right)^{\frac{1}{\bar{\tau}_{F\mathcal{M}}}} \qquad \bar{\tau}_{F\mathcal{M}} = \frac{\sum_{M\in\mathcal{M}} \tau_{FM}}{\sum_{M\in\mathcal{M}} 1}$$

Similarly, for men

$$\bar{V}_{\mathcal{F}\mathcal{I}M\mathcal{J}} = \bar{V}_{00M\mathcal{J}} + \bar{V}_{\mathcal{F}0M0} - V_{00M0} - \tau_{0M}\ln\bar{Y}_{00M\mathcal{J}} + \tau_{\mathcal{F}M}\ln\bar{C}'_{\mathcal{F}\mathcal{I}M\mathcal{J}} + \sum_{I\in\mathcal{I}} 1$$

where $\bar{U}_{00M\mathcal{J}} = \ln\big(\sum_{J\in\mathcal{J}} e^{V_{00MJ}}\big)$, $\qquad \bar{V}_{\mathcal{F}0M0} = \ln\big(\sum_{F\in\mathcal{F}} e^{V_{F0M0}}\big)$, $\quad \bar{Y}_{00M\mathcal{J}} = \Big(\frac{\sum_{J\in\mathcal{J}} e^{V_{00MJ}} Y_{00MJ}^{-\tau_{0M}}}{\sum_{J\in\mathcal{J}} e^{V_{00MJ}}}\Big)^{\frac{-1}{\tau_{0M}}}$

$$\bar{C}'_{\mathcal{F}\mathcal{I}M\mathcal{J}} = \left(\frac{\sum_{J\in\mathcal{J}} e^{V_{00MJ}} Y_{00MJ}^{-\tau_{0M}} \sum_{F\in\mathcal{F}} e^{V_{F0M0}} \sum_{I\in\mathcal{I}} C'^{\tau_{FM}}_{FIMJ}}{\sum_{J\in\mathcal{J}} e^{V_{00MJ}} Y_{00MJ}^{-\tau_{0M}} \sum_{F\in\mathcal{F}} e^{V_{F0M0}} \sum_{I\in\mathcal{I}} 1}\right)^{\frac{1}{\bar{\tau}_{\mathcal{F}M}}}$$

Thus, average consumption in an aggregate category is the weighted generalized mean of consumption in its sub-categories. Using the estimated $\bar{C}_{F\mathcal{I}\mathcal{M}\mathcal{J}}$ and $\bar{C}'_{\mathcal{F}\mathcal{I}M\mathcal{J}}$, we can compare the sum of *economic* return to education coming from labor and marriage markets.

However, the returns also have non-economic components that are not transferable between partners. For example,

$$\begin{aligned} r^m_{F_1F_2M} &= \bar{U}_{F_2,+,M,+} - \bar{U}_{F_2,+,0,0} - \bar{U}_{F_1,+,M,+} + \bar{U}_{F_1,+,0,0} \\ &= U_{F_20M0} - U_{F_2000} - U_{F_10M0} + U_{F_1000} \qquad \text{(non-economic marriage return)} \\ &\quad + \tau_{F_2M}\ln\bar{C}_{F_2+M+} - \tau_{F_20}\ln\bar{C}_{F_2+00} - \tau_{F_10}\ln\bar{C}_{F_1+M+} + \tau_{F_10}\ln\bar{C}_{F_1+00} \qquad \text{(economic marriage return)} \\ r^m_{F_1F_2I} &= \bar{U}_{F_2,I,+,+} - \bar{U}_{F_2,0,+,+} - \bar{U}_{F_1,I,+,+} + \bar{U}_{F_1,0,+,+} \\ &= U_{F_2I00} - U_{F_2000} - U_{F_1I00} + U_{F_1000} \qquad \text{(non-economic employment return)} \\ &\quad + \bar{\tau}_{F_2+}\ln\bar{C}_{F_2I++} - \tau_{F_20}\ln\bar{C}_{F_20++}\frac{Y_{F_2I00}}{\bar{Y}_{F_2000}} - \bar{\tau}_{F_1+}\ln\bar{C}_{F_1I++} + \tau_{F_10}\ln\bar{C}_{F_10++}\frac{Y_{F_1I00}}{\bar{Y}_{F_1000}} \qquad \text{(economic return)} \end{aligned}$$

Then $\bar{Y}_{F+M+} = \bar{C}_{F+M+} + \bar{C}'_{F+M+}$, and the aggregate sharing rule becomes

$$\bar{\rho}_{FM} = \Big(1 + \exp\big(\frac{\bar{V}_{F+M+} - V_{F0M0} - \bar{B}'_{M+} - \bar{U}_{F+M+} + U_{F0M0} + \bar{B}_{F+}}{\tau_{FM}}\big)\Big)^{-1} \tag{37}$$

In this regard, the marriage return conditional on spouse type becomes

$$
\begin{aligned}
r^m_{F_1F_2M} &= \bar{U}_{F_2,+,M} - \bar{U}_{F_2,+,0} - \bar{U}_{F_1,+,M} + \bar{U}_{F_1,+,0} \\
&= \tilde{r}^m_{F_1F_2M} + \tau_{F_2M}\ln C_1^{F_2,+,M} - \tau_{F_1M}\ln C_1^{F_1,+,0} - \tau_{F_20}\ln C_1^{F_1,+,M} + \tau_{F_10}\ln C_1^{F_2,+,0}
\end{aligned}
$$

where $\tilde{r}^m_{F_1F_2M} = U_{F_20M0} - U_{F_10M0} - U_{F_200} + U_{F_100}$ is the non-transferable component of marriage return. With the first order approximation around $\bar{C}_{1F_1F_2M} = \frac{1}{4}(C_1^{F_2,+,M} + C_1^{F_1,+,M} + C_1^{F_2,+,0} + C_1^{F_1,+,0})$, we can write

$$
r^m_{F_1F_2M} \approx \tilde{r}^m_{F_1F_2M} + (\tau_{F_2M} - \tau_{F_1M} - \tau_{F_20} + \tau_{F_10})\ln \bar{C}_{1F_1F_2M} + \frac{\bar{\tau}_{F_1F_2M}}{\bar{C}_{1F_1F_2M}}(C_1^{F_2,+,M} - C_1^{F_1,+,M} - C_1^{F_2,+,0} + C_1^{F_1,+,0}) \tag{38}
$$

where $\bar{\tau}_{F_1F_2M} = \frac{1}{4}(\tau_{F_2M} + \tau_{F_1M} + \tau_{F_20} + \tau_{F_10})$.

Using the expected utilities we can find average sharing rule by the education of couples as

$$
\bar{\rho}_{FM} = \left(1 + \exp\left(\frac{\bar{V}_{M,+,F} - V_{F0M0} - \bar{U}_{F,+,M} + U_{F0M0}}{\tau_{FM}}\right)\right)^{-1}
$$

4 Data

In this section, we describe the datasets used for estimation. The random samples of U.S. households are drawn from IPUMS (Ruggles et al., 2020) and consist of two sources: Census extracts for the years 1960, 1970, 1980, 1990, and 2000; and the American Community Survey (ACS) for 2001–2019. To ensure large sample sizes, we utilize IPUMS's 5-year ACS datasets for 2005–2009, 2010–2014, and 2015–2019, centering them on their midpoints (2007, 2012, and 2017). The complete list of U.S. datasets and their respective sample sizes is provided in Appendix Table A.2.

Marriage is defined using the standard IPUMS classification, based on self-reported relationships to the household head as "spouse". Additionally, we restrict the sample to single and married households where the woman is aged 30–60 or the man is aged 32–62. This age range captures the period when education is typically completed, and marriage and labor force participation rates are more stable (see Figure 1 in Chiappori, Costa Dias, and Meghir, 2020).

4.1 Classifications of education and occupation

The classifications of marriage and employment include null categories for single and non-working individuals who are not matched, alongside ranked groups for those who are matched. When working with ordinal discrete data, the selection of categories for ordered variables is guided by several considerations. On the one hand, more finely tuned categorizations can improve statistical power for detecting associations (Agresti, 2010). On the other hand, models that rely on odds ratios require all elements of the contingency table to be non-zero, which limits the feasibility of detailed classifications for education and occupation.[7]

Furthermore, for ordinal scales, unlike "interval scales", the absolute distances between categories are unknown, and categories must be chosen to create sufficient contrast between groups. When categorizing multiple variables with differing characteristics (e.g., spouse types and job types), it is also crucial to ensure that the marginal distributions of the variables are comparable within a given context. If one variable has finer categorization in the lower tail of its distribution while the other has finer categorization in the upper tail, aggregate association measures can be distorted due to the non-homogeneity of classifications.

Considering these criteria, in our main analysis, we categorize the U.S. educational attainment codes from IPUMS into five groups:

1. *Dropouts (D)*: Individuals with less than 12 years of education or without a high school qualification.
2. *High school (H)*: Individuals who completed high school.
3. *Some college (C)*: Individuals with 1 to 3 years of college education or with an associate's degree.
4. *Bachelor's (B)*: Individuals with a bachelor's degree.
5. *Graduate (G)*: Individuals with education beyond a bachelor's degree.

For occupations, the U.S. data follows the Standard Occupational Classification (SOC) system, which is converted to the International Standard Classification of Occupations (ISCO) using the correspondence table provided by the U.S. Bureau of Labor Statistics (BLS). Based on the first-digit ISCO coding system, we group occupations into four categories:

1. *Unskilled (U)*: Elementary occupations (code 9).
2. *Skilled (S)*: Skilled or semi-skilled workers (codes 0, 4 to 8).
3. *High skilled (H)*: Technicians and associate professionals (code 3).
4. *Professional (P)*: Managers and professionals (codes 1 and 2).

Figure 2 illustrates the changes in population distribution by education level, job type, and spouse education for women (top panel) and men (bottom panel) across various years. Between 1960 and 1990, there is a significant decline in the number of individuals who dropped out of high school, accompanied by a significant increase in the share of those with college degrees or higher, for both genders. After 2000, these population shares remained relatively stable. Regarding job types, the data reveals a sharp rise in the proportion of women employed in skilled, high-skilled, and professional jobs between 1980 and 2000, with little variation in these shares before and after this period.

[7] Zero elements are particularly likely when sample sizes are small. For instance, it is rare to observe a working woman with a university degree marrying an illiterate, non-working man in small samples.

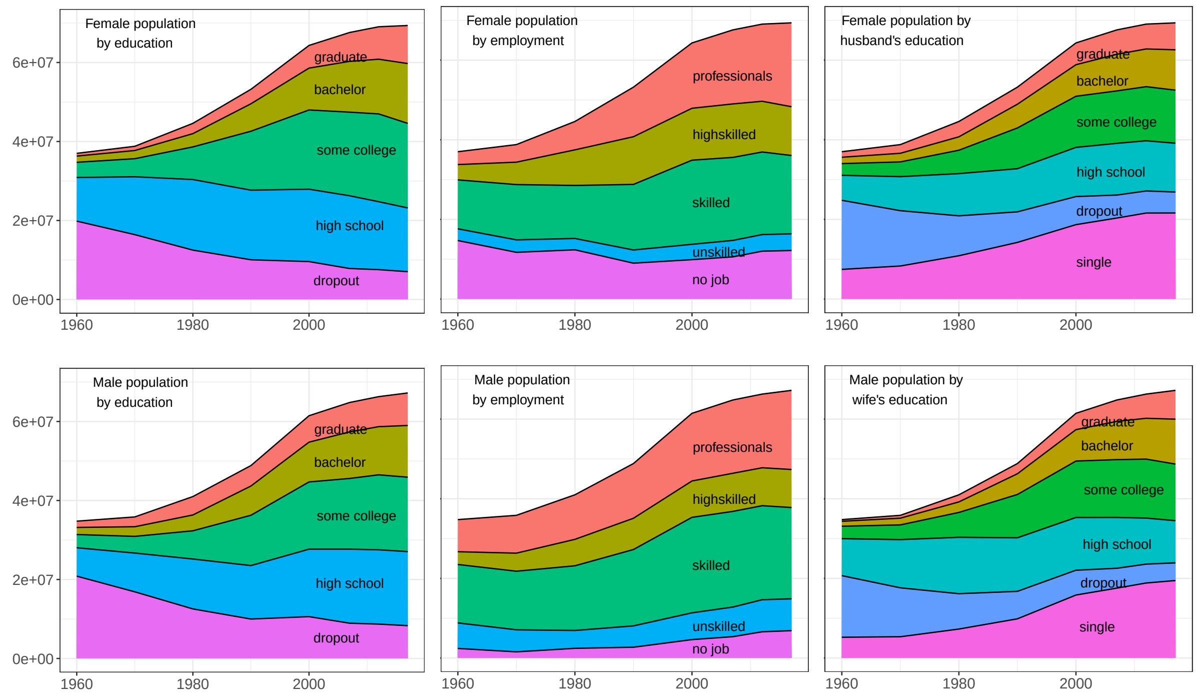


Figure 2: Female and male population by education, employment, and marital status

Appendix Table A.6 presents the matching tables for each year. Except for few cases in 1960 and 1970 (which has smaller sample size), there are no missing elements in the tables for the other years. A common approach for handling zero counts in contingency table analysis is to replace zeros with 0.5 (see Section 2.5.2 of Kateri, 2014). Another alternative is to use more aggregated classifications that eliminate zeros. In our main analysis, we retain the detailed classifications and replace zeros with 0.5 for the 1960 and 1970 data. For robustness checks, we employ more aggregated classifications.

For each element of the population distribution where at least one partner is employed, we calculate inflation-adjusted mean and variance of yearly household earnings using IPUMS's *INCWAGE* variable, which reports total pre-tax wage and salary income for the previous year.[8] Appendix Figure A.2 depicts the average earnings ratios for various job and spouse types compared to their mean to assess whether the classifications effectively differentiate between categories. The results show upward trends for both job and spouse classifications, with the highest-ranking categories displaying similar earnings ratios.

In parallel with the population contingency table, we construct two four-dimensional arrays for each year, containing the average earnings and variance of earnings by type. Missing earnings data from 1960 and 1970 are imputed using the average earnings of jobs, conditional on the partner's education. Missing values for the variance of earnings are replaced by the maximum variance of jobs, conditional on the partner's education. These three arrays (population, earnings, and earnings variance) are used to estimate the overidentified model with heteroskedastic unobservables, as described in Section 3.

With five education categories and four occupation categories, the model incorporates 511 degrees

[8]Earnings values are adjusted using the Consumer Price Index (CPI) provided by the Bureau of Labor Statistics (BLS), expressed in 1983 dollars.

of freedom. The estimated parameters of the over-identified model (36) that are of primary interest are presented in the Appendix: Table ?? for A_{FM} and B_{FM}, Table A.3 for τ_{FM}, and Table ?? for σ_F and σ_M.

5 Marriage and employment returns to education in the U.S.

We start presenting our empirical findings by discussing the trends for the marriage return conditional on spouse education ($r^m_{F_1F_2H}, r^m_{M_1M_2W}$) and the employment return conditional on job classification ($r^e_{F_1F_2I}, r^e_{M_1M_2J}$) and evaluate the equivalent dollar values of different spouse types. Afterwards, we present the findings regarding the aggregate measures for the return to education.

5.1 Conditional returns

Figure 3 illustrates the marriage return to education for high school level and above compared to dropouts, across various spouse types as defined in equation (19). The returns are expressed in terms of log odds ratios, indicating the extent to which the log odds of marrying a specific spouse type, rather than remaining single, are greater for individuals with different education levels compared to those of the same gender who dropped out of high school.

The top panel of Figure 3 presents the conditional marriage return for women by their husband's education level. The results reveal that marrying up (i.e., marrying a more educated husband) consistently yields positive marriage returns for women, while negative returns may occur only in cases of "marrying down". However, not all instances of marrying down result in negative returns. Notably, women with a graduate degree who marry a husband with a bachelor's degree experience significantly positive returns in all years. Similarly, women with a bachelor's degree who marry a husband with some college education also see positive returns. This finding aligns with Low (2023), which suggests a non-monotonic relationship between a woman's education and the quality of her husband due to the trade-off between fertility and investment in human capital. Consequently, women at the very top of the human capital distribution tend to marry down, on average, compared to women with slightly lower human capital levels.

Another observation relates to the marriage return for women with a high school education compared to higher education levels. In earlier years, high school-educated women marrying up to a husband with a bachelor's or graduate degree experienced significantly higher surplus shares. However, in recent years, their marriage return has become comparable whether they marry a husband with the same education level or marry up. This trend indicates that the surplus from marrying up has declined over time for this group.

Additionally, marrying a graduate degree husband consistently produced significantly positive returns for women at all education levels in 1960. Over time, however, the surplus share for less-educated women marrying a graduate degree husband has declined, while for women with a graduate degree, it has slightly increased. This pattern highlights the growing importance of assortative matching in generating higher gains at the upper end of the educational distribution.

The bottom panel of Figure 3 presents the trends in marriage returns for men. In contrast to women, marrying up does not always yield positive returns for men. Notably, until 2000, men with a bachelor's degree or lower did not exhibit a preference for marrying a graduate degree wife over a bachelor's degree wife. Only men with a graduate degree consistently preferred a graduate degree wife over less-educated spouses. Overall, this trend suggests a weakening of the breadwinner norm at the top of the educational distribution, where men traditionally preferred to be the primary earners in the household and marry a woman with lower income. The increasing acceptance of highly educated wives after 2000 indicates a shift in marriage market dynamics, potentially reflecting changes in gender roles and the growing economic contributions of women within households. Supporting evidence for this shift comes from Figure A8 of Low (2023), which shows that the spousal income gap between graduate- and college-educated women in the U.S. was negative until 1990 but became significantly positive after 2000.

Returns associated with marrying a spouse with a high school diploma or some college education show less variation across educational groups for men than for women, particularly in the first four data rounds. The lower slope suggests that in couples where the wife has a high school or some college degree and the husband has higher education, the woman is often either not working or serving as the secondary earner in the household, which means her education level has a smaller impact on household income compared to the education level of the husband. As a result, the men's return conditional on wife's education is less decreasing in their own education that women's return conditional on husband's education.

Figure 4 illustrates the employment returns to different educational groups compared to dropouts, conditional on occupation type. For women, the return to education is highest for professional jobs, with the log odds ratio of obtaining a professional job increasing with educational attainment relative to dropouts. The return to education follows a clear ranking: high-skilled jobs yield higher returns than skilled jobs, which in turn yield higher returns than unskilled jobs. Notably, the trend of log odds ratios is slightly decreasing for high-skilled jobs, and it becomes more negative and declining for skilled and unskilled jobs. Importantly, the return to education for unskilled jobs is negative for all education levels, suggesting that women with at least high school education gain more by staying out of the labor force than by working in unskilled jobs, relative to dropouts. A similar pattern is observed for skilled jobs before 1980, but after this period, the returns start to rise.

The bottom panel shows the conditional employment returns for men. Similar to women, higher education yields higher returns in jobs with greater skill requirements. However, after 1990, high school-educated men show a preference for working in unskilled jobs over not working, in contrast to women. Additionally, the absolute magnitude of employment returns is generally lower for men than for women, suggesting that education plays a more crucial role in determining employment and job quality for women than for men.

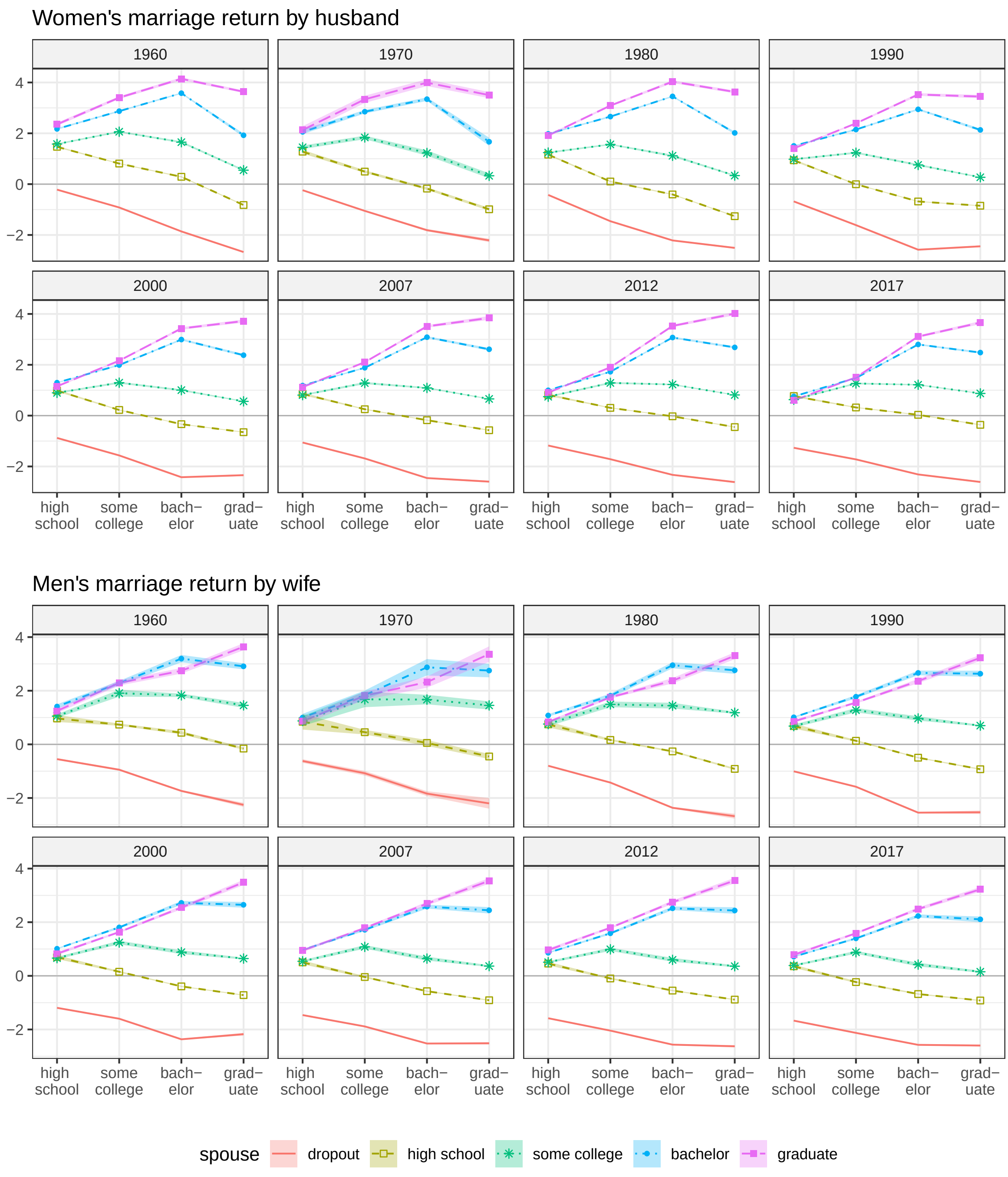


Figure 3: Marriage returns to education conditional on spouse education over time in the U.S. The indices are $\hat{r}^m_{F_1F_2M}, \hat{r}^m_{M_1M_2F}$ for different spouse types. The shaded areas are the confidence intervals.

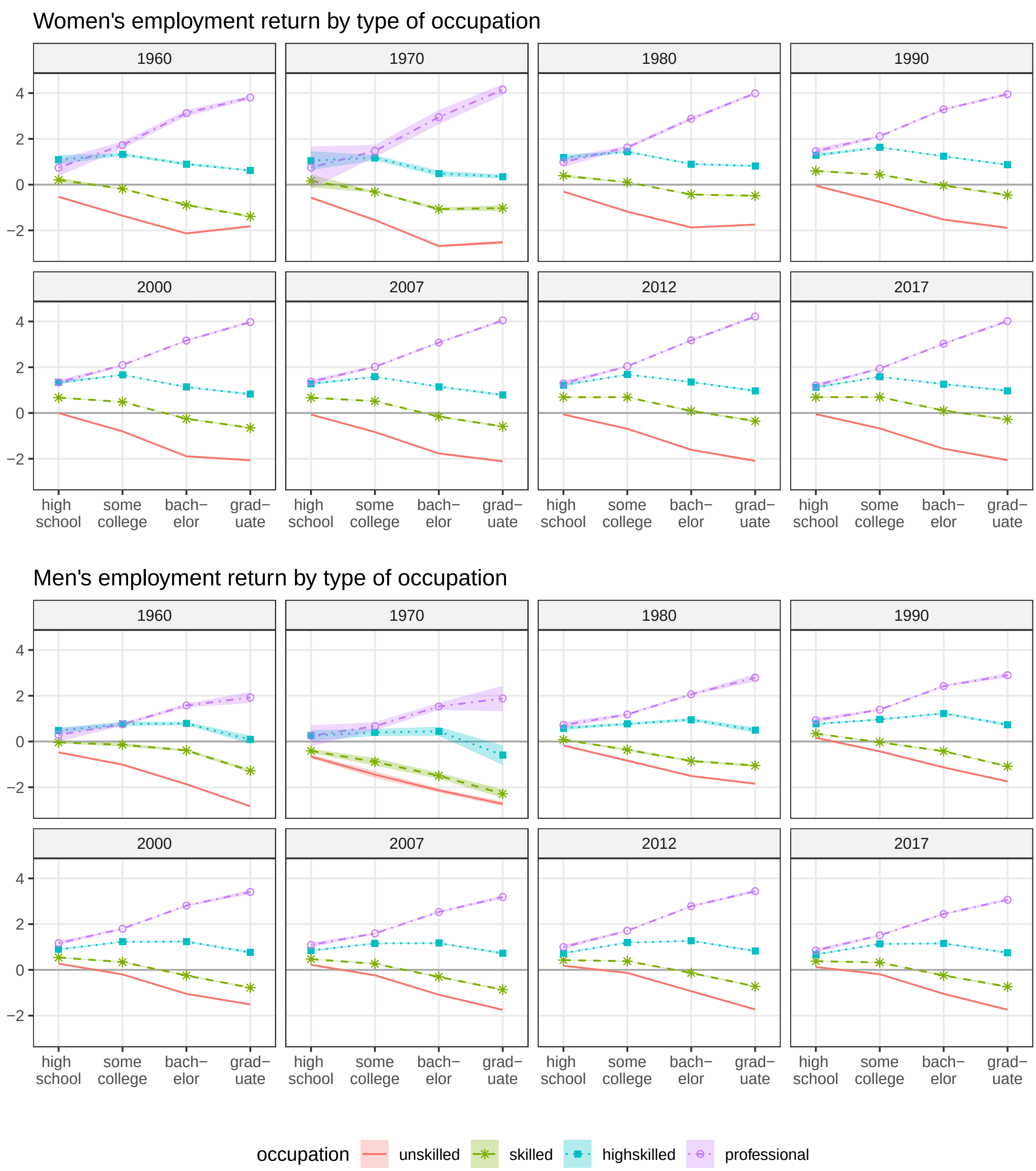


Figure 4: Employment returns to education conditional on occupation type over time in the U.S. The estimated indices are $\hat{r}^e_{F_1 F_2 I}$ and $\hat{r}^e_{M_1 M_2 J}$ for different job types. The shaded areas are the confidence intervals.

In Figures 3 and 4, we generally find small standard errors of the return indices, except for the cases with relatively low population, such as estimations for the year 1970 with a notably lower sample counts (Online Appendix Table A.2). The reason for this pattern is the variance of population moments (35) that, as described in Appendix A.6, is proportional to the inverse of the sample size of the corresponding educational cohorts.

5.2 Aggregate returns in the U.S.

n Figure 5, we present the trends of the aggregate extensive and intensive margin indices as defined in (20) to (30). Unlike Figures 3 and 4, which depict the cumulative impact of education from dropout to higher levels, this figure focuses on the incremental returns of each educational step relative to the one lower level. Given our five educational categories, we analyze four transitions: dropouts to high school, high school to some college, some college to bachelor's, and bachelor's to graduate school. By examining these stepwise returns, we can better understand how the gains from education in both the marriage and job markets evolves at each stage.

The top row of Figure 5 displays the trends in marriage returns across educational transitions. For the shift from dropout to high school, both men and women exhibit similar trends, with women experiencing slightly higher returns. For individuals who attended some college, the marriage return is negative for women in all years except 2017, whereas it is positive for men except in 1980. However, for both genders, the marriage return to some college relative to high school shows an increasing trend from 1980 onward. The marriage return to a bachelor's degree is consistently positive for men. For women, it starts at negative values but follows an upward trend, eventually aligning with men's returns after 1970.

For individuals with graduate-level education, the marriage return initially appears negative for both men and women, with significantly larger negative values for women. Over time, however, the trend rises, turning positive for men after 1990, while remaining negative for women up to 2012. These trends suggest that, historically, highly educated women faced substantial relative marriage penalties. However, this pattern has reversed in recent decades. Our findings on women's marriage return indices align with Figure 21 of Chiappori et al. (2017), further confirming the evolving role of education in shaping marital outcomes.

The second row of Figure 5 presents employment returns to education across adjacent educational groups. While obtaining a high school diploma has consistently yielded positive employment returns for both genders, its value was substantially higher for men before 2000. The employment return to some college education follows a similar increasing trend for both genders. For a bachelor's degree, the employment return has always been positive, but it exhibits diverging trends: increasing for men while decreasing for women between 1960 and 2007. In contrast, graduate education has significantly higher employment returns for women in all years. On average, the log odds ratio of employment for women with graduate degrees is about 0.8 units higher than for those with a bachelor's degree, indicating that the odds of employment for graduate-educated women are approximately 2.2 times higher than for women with a bachelor's education. This suggests that while graduate education increasingly strengthens women's labor market attachment, the relative impact of a bachelor's degree has declined over time.

The aggregate joint return to education at the extensive margin is illustrated in the third row of Figure 5. With the exception of women with some college and graduate education in 1960, the joint extensive margin return is positive across all years and educational levels. Moreover, aside from high school education, which yields significantly higher returns for women, the trends and magnitudes of the joint return are quite similar for men and women across the other educational categories.

The fourth row of Figure 5 illustrates the difference between marriage and employment returns to education. For the transition from dropout to high school, this difference is consistently negative for men and turns negative for women after 1980. This suggests that high school education improves both marriage and employment prospects for both genders, its relative benefit in employment is higher, particularly for men. For some college education, the difference is initially positive for men but turns negative after 1980, while for women, it remains negative throughout. This indicates that the return to some college education in the labor market participation surpasses its return in the marriage market participation.

For the transition from some college to a bachelor's degree, the difference is always negative for men, implying that employment returns consistently exceed marriage returns. For women, however, the difference starts negative but follows an increasing trend, becoming positive after 1980. This shift suggests that for women, in contrast with men, the relative return to a bachelor's degree in the marriage market raises above its return in the labor market over time.

For graduate education, the difference between marriage and employment returns starts with a significantly negative log odds ratio for women and a more moderately negative value for men. After 1980, the trend becomes increasingly positive for both genders, turning positive for men but remaining significantly negative for women. This indicates that while graduate education enhances employment prospects for both men and women, its relative benefits in the marriage market remain weaker for women, even as the gap narrows over time.

The fifth row of Figure 5 presents the aggregate spouse return to education, conditional on being married. The consistently positive and significant values for both genders indicate a monotonic relationship between education and spouse quality: higher education levels are associated with higher-quality spouses. However, an exception arises for graduate-educated women before 2000, where their spouse return is near zero. This pattern aligns with Figure 3, which shows that during this period, men with lower education levels did not prefer graduate-educated women over those with a bachelor's degree. As a result, the average spouse return for graduate-educated women remained near zero in those years.

The sixth row of Figure 5 illustrates the trend of job return to education, conditional on being employed. We observe that the relationship between education and job return remains relatively stable over time for all education categories, and it follows a monotonic pattern such that higher education consistently yields higher job returns. Notably, job return is higher for women at lower levels of education, but for bachelor's and graduate education, the trends is either nearly identical or slightly higher for men. This suggests that the differences in conditional returns observed in Figure 4 between men and women primarily stem from the lower education levels. When the benchmark is dropout, these differences accumulate over successive education levels, leading to the observed gap in returns at the bachelor's and graduate levels.

Although the two intensive margins of the returns remain positive across all years, they exhibit two distinct patterns as education levels increase. The mean level of spouse return decreases from the left graph to the right, while the mean level of job return increases, particularly in recent years. This pattern suggests that education has an increasing and concave relationship with spouse quality but an increasing and convex relationship with job quality. Consequently, at the bottom row of Figure 5, we observe positive differences between spouse and job returns for high school education, whereas for graduate education, the difference turns negative after 1980. For some college and bachelor's degrees, the difference remains around zero, indicating that at these education levels, the trade-off between spouse and job returns is more balanced.

The seventh row of Figure 5 presents the joint return to education at the intensive margin. While the values are positive and relatively stable over time up to the graduate level, women exhibit higher joint returns than men for high school and some college education, and the returns are nearly identical at the bachelor's level. For graduate education, the joint return is consistently positive for men. In contrast, for women, it declines initially, turns negative in 1970 and 1980, and then begins to rise after 2000, eventually surpassing the joint return for graduate-educated men after 2010. The observed pattern of higher joint returns to college education for women at both margins after 1980 aligns with the rise of female educational attainment and the reversal of the college gender gap in the U.S., as documented by Goldin et al. (2006).

In Online Appendix Figure A.3, we estimate the model using alternative classifications for education and occupation. Qualitatively, the levels and trends of the returns for the new classifications are combinations of those for the categories that are merged to create them. In the top panel, where we only change the classification of occupation, we observe little changes in the marriage and spouse returns. For employment and job returns, the trends are similar, and the curves slightly shift upward or downward. The bottom panel shows the change in education classification, where both individuals and spouse types change. We observe that the trend of the returns for the merged classifications of education reflects the average of their split classifications.[9]

[9]In unreported graphs, we change only the spouse's education classification and find a similar trend as the top panel of Online Appendix Figure A.3, with the difference that the employment and job returns do not show any change, but the marriage and spouse return curves move upward or downward with similar trends over time.

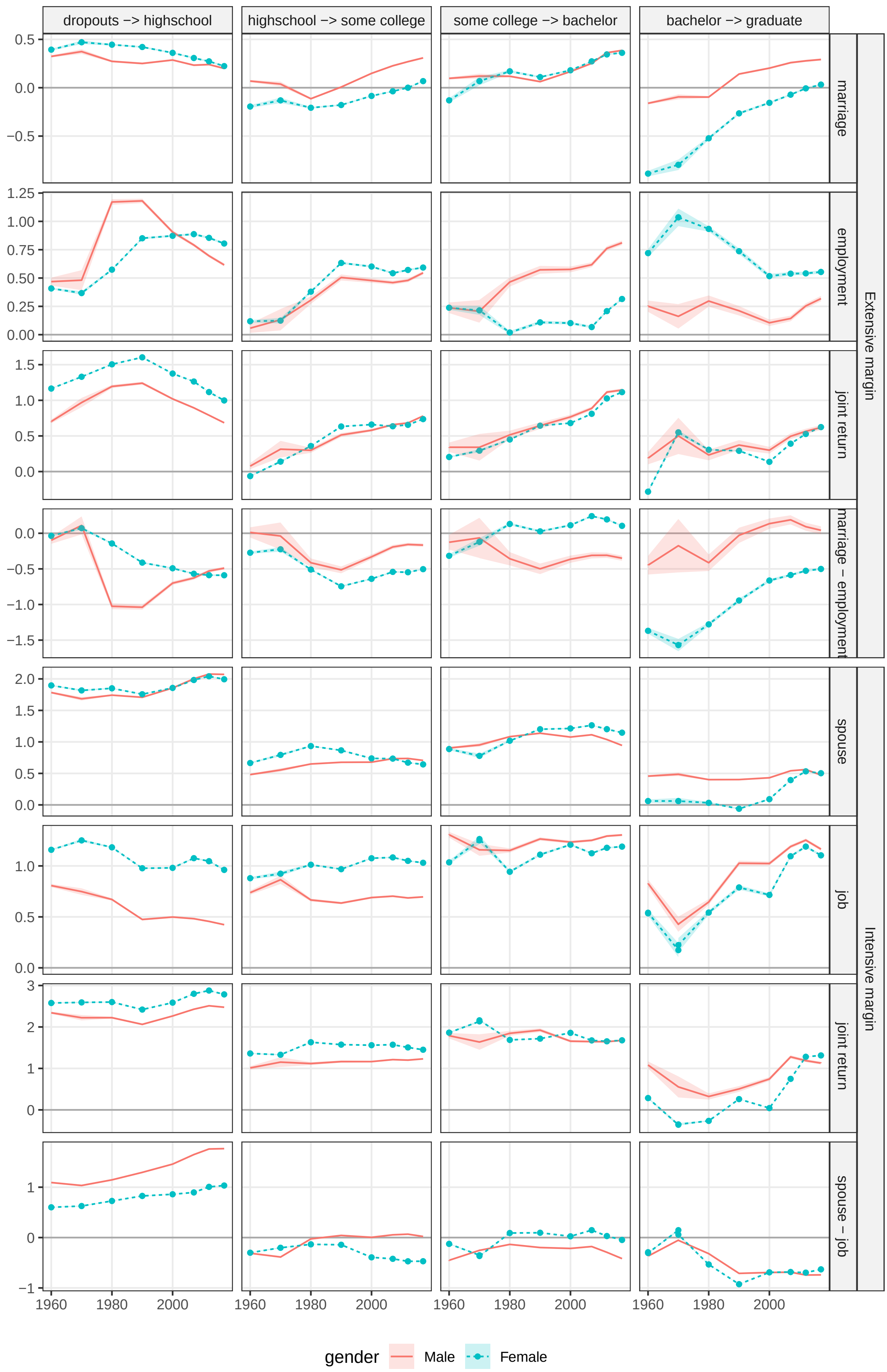


Figure 5: The trends of aggregate returns to education and their differences in the U.S. The indices for the extensive margin are r^m, r^e, and δ^{me}. The indices for the intensive margin are r^s, r^j, and δ^{sj}.

5.3 Dollar values of Spouse Education

Using the estimated parameters listed in Appendix Tables ?? and A.3 for different years, we can interpret the return indices in dollar terms. Since all conditional return indices are based on difference-in-differences of deterministic utilities, we can convert them into earnings units for all conditional job returns and for marriage and spouse returns when at least one partner is employed. However, this conversion is not possible for employment returns or marriage and spouse returns involving non-working individuals. In these cases, the deterministic utility differences do not directly map to monetary transfers, making it infeasible to express them in earnings units.

Table 2 presents the dollar-valued estimates of r^m_{1FH} and r^m_{1MW} in both 1983 USD and as a percentage of the annual earnings of the corresponding educational cohort of women and men in 1960 and 2017. The dollar unit index reflects the equivalent compensation for marrying a spouse with education level H (for women) or W (for men), relative to remaining single, for individuals with education level F_2 (women) or M_2 (men), compared to those with education level F_1 (women) or M_1 (men). Essentially, these estimates quantify the additional value of marrying different spouse types compared to dropouts.

For women, consistent with Figure 3, the estimated numbers in Table 2 suggest that, compared to dropouts, single women in all educational cohorts are willing to forgo a share of their earnings in exchange for a husband with higher education than themselves. In contrast, the first rows of the two years indicate that marrying a dropout husband yields negative returns for all educational groups. Notably, the most negative impact is for women with bachelor's degrees in 2017, who would pay approximately 13 percent of their earnings, in addition to what a dropout woman would pay, to remain single rather than marrying a husband without a high school education.

A husband with a high school education is more attractive for women with high school diplomas and some college education than dropout women and they would pay about 2-3 percent of their annual earnings for that. For women with bachelor's degrees, the preference for marrying a high school-educated husband is similar to that of dropout women, with the equivalent compensation around zero. However, women with graduate degrees would pay roughly 2 percent of their annual earnings, aside from the amount a dropout woman pays, to avoid marrying a husband with only a high school education. The compensation for marrying a husband with some college education or higher is positive across all educational levels, indicating that, compared to dropout women, all other categories would willingly give up a portion of their earnings to enter such a marriage. The willingness to forgo earnings also holds for marriages with husbands holding bachelor's and graduate degrees with larger compensation values.

Converting the 2017 estimates to 2023 prices ($\approx$ 3 times of the 1983 USD), the numbers suggest that relative to dropout women, women with bachelor's degrees would pay around \$3,700 yearly to marry a husband with some college education, and slightly over \$9,600 yearly to marry a husband with bachelor's or graduate degrees rather than remaining single. Moreover, in 2017, women with graduate degrees would annually spend around 16 percent of their earnings, which equates to approximately \$14,000 in 2023, to

Table 2: Estimation of equivalent annual enumeration of marrying different spouses across different educational cohorts of employed individuals. ΔY is measured in 1983 U.S. dollars.

	year	spouse type	equivalent annual compensation ΔY				percent of yearly earnings $\Delta Y/Y$			
			HS	SC	B	G	HS	SC	B	G
female	1960	dropout	-44	-272	-645	-989	-0.54	-3.06	-5.48	-6.17
		high school	185	243	92	-353	2.31	2.74	0.78	-2.20
		some college	198	618	522	279	2.47	6.96	4.43	1.74
		bachelor	260	783	1113	768	3.24	8.81	9.44	4.80
		graduate	270	909	1268	1602	3.36	10.23	10.76	10.00
	2017	dropout	-464	-1319	-2469	-2297	-4.32	-9.98	-12.58	-8.43
		high school	314	223	-102	-514	2.92	1.69	-0.52	-1.89
		some college	256	973	1238	817	2.38	7.37	6.31	3.00
		bachelor	298	1064	3149	2874	2.77	8.06	16.04	10.55
		graduate	207	947	3276	4610	1.92	7.17	16.70	16.92
male	1960	dropout	-200	-879	-1939	-2022	-1.03	-3.97	-7.08	-7.55
		high school	366	729	521	-185	1.88	3.29	1.90	-0.69
		some college	404	1929	2365	1449	2.07	8.71	8.64	5.41
		bachelor	543	2337	4201	2981	2.78	10.55	15.34	11.14
		graduate	469	2306	3490	3596	2.40	10.41	12.74	13.44
	2017	dropout	-390	-2627	-4918	-4850	-2.32	-12.32	-14.87	-11.54
		high school	89	-347	-1652	-2224	0.53	-1.63	-4.99	-5.29
		some college	101	1198	825	97	0.60	5.62	2.49	0.23
		bachelor	196	2045	5809	5652	1.16	9.59	17.56	13.44
		graduate	213	2284	6494	8776	1.27	10.71	19.63	20.88

marry a husband with the same educational background instead of remaining single.

The pattern for men in Table 2 closely mirrors that of women, but with higher values in both dollar terms and percentage terms. This suggests that the "price" of an educated woman in the marriage market is significantly higher than that of a man with the same education level. For instance, in 2017 and at 1983 USD terms, a man with a graduate degree would pay \$8,776 to marry a woman with the same degree, whereas a woman with a graduate degree would pay only \$4,610 to marry a man with similar education, compared to remaining single. This gender disparity in spouse valuations can help explain the widening college gender gap in the U.S., where women's higher education attainment has surpassed men's over recent decades (Goldin et al., 2006; Becker et al., 2010). Additionally, consistent with Figure 3, we find that in 1960, a bachelor's degree wife is valued higher than a graduate degree wife by men with any education level except graduate degree holders. However, by 2017, a graduate degree wife was valued above a bachelor's degree wife across all educational groups.

Table 2 also allows us to compare the equivalent values of various husbands or wives by calculating the differences between their corresponding rows. For instance, the difference between the final and initial rows of each year indicates the worth of marrying a spouse with a graduate degree instead of a high school dropout spouse, for each educational group relative to dropouts. In 2017 and in terms of 2023 prices, this number roughly amounts to \$2,000 for high school-educated women, \$6,800 for women with some college education, \$17,200 for women with bachelor's degrees, and \$20,700 for women with graduate degrees. The corresponding numbers for men in 2017 are \$1,800, \$14,700, \$34,200, and \$40,900.

To illustrate better the spouse return over time, in Table 3, we estimate the equivalent annual remuneration of improving the type of spouse from high school degree to bachelor's degree over various years.

Table 3: Estimation of equivalent yearly compensation of husband change from high school to bachelor's across different educational groups of *employed* women. ΔY is measured in 1983 U.S. dollars.

	year	equivalent annual compensation ΔY				percent of yearly earnings $\Delta Y/Y$			
		HS	SC	B	G	HS	SC	B	G
female	1960	75	540	1020	1121	0.94	6.07	8.66	7
	1970	74	481	1169	1637	0.79	4.85	8.43	8.12
	1980	75	642	1953	2176	0.86	6.58	17.17	12.89
	1990	154	1252	2905	2722	1.55	10.48	18.66	12.64
	2000	57	905	2725	3334	0.54	6.94	15.17	14.18
	2007	114	1149	3336	3900	1.03	8.43	17.62	14.97
	2012	30	987	3094	3620	0.29	7.73	16.55	13.9
	2017	-16	842	3251	3389	-0.15	6.37	16.57	12.43
male	1960	177	1608	3680	3165	0.91	7.26	13.44	11.83
	1970	119	1688	4820	3759	0.51	6.36	13.78	10.56
	1980	197	2056	5206	5991	0.91	8.57	17.28	19.61
	1990	124	2155	5848	6377	0.63	9.35	19.87	18.2
	2000	94	2229	6161	7805	0.51	9.99	20.06	20.9
	2007	192	2470	7539	8999	1.06	10.84	22.23	20.79
	2012	83	2073	7294	8366	0.51	10.05	22.71	20.35
	2017	107	2392	7462	7876	0.63	11.22	22.55	18.73

The estimated numbers highlight how much individuals in each educational category value a spouse with a bachelor's degree vs. a spouse with a high school degree compared to dropout individuals. We observe that in both genders, individuals with a high school degree have the smallest equivalent remuneration which in most years is below one percent of their annual earnings. These low numbers for high school graduates suggest two interrelated channels: first, their preference for highly educated spouses does not substantially different from that of high school dropouts; second, it potentially reflects a preference towards assortative matching within this group. A stronger indication of assortativeness emerges within the bachelor's degree holder category. Across all years, individuals with bachelor's degrees would exchange the highest percent of their income (often also the highest dollar values) for a partner with a similar educational background rather than a high school-educated partner.

5.4 Non-Economic and Economic Components of the Returns

to be completed

6 Conclusion

This paper extends the frictionless matching framework of Choo and Siow (2006) by considering the joint decision of individuals in two bilateral markets. This approach allows for the joint estimation of different components of marriage and employment returns, and enables comparison between them. These components have two margins: an extensive margin reflecting the overall gain from marriage and employment compared to singlehood and non-participation, respectively, and an intensive margin that reflects the quality of match conditional on matching. The empirical strategy incorporates earnings data from the labor market as additional moments to estimate the model. A great advantage of this method is its low data requirement that allows for evidence over time and across space using cross-sectional household surveys.

The study uses U.S. cross-sectional household data to analyze trends in these returns. For women, marrying a more educated spouse consistently yields positive marriage returns. However, until 2000, men with a bachelor's degree or lower did not prefer marrying a graduate-degree woman over a less educated woman, but this pattern has reversed in recent decades. Higher education leads to higher returns in jobs with greater skill requirements for both genders. The aggregate indices suggest that while attending college does not greatly affect the odds of employment, the marriage return has been positive and increasing over the past 20 years. Graduate education has the highest employment return at both margins. In addition, the intensive margin indices suggest that as education increases, the quality of spouse improves at a decreasing rate, while job quality improves at an increasing rate.

The study provides dollar-valued estimates of marriage returns, suggesting that women with bachelor's degrees in 2017 were willing to forgo about 16 percent of their earnings to marry a man with a bachelor's degree or above, rather than remain single. This number for men is about 20 percent of their earnings, suggesting that the "price" of an educated woman in the marriage market is significantly higher than that of a man with the same education level.

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APPENDIX

A Mathematical Appendix

	m_1	m_2	m_1	m_2	m_1	m_2	m_1	m_2	
f_1			1	0	0	0	0	0	j_1
f_2			0	0	0	0	0	0	
f_1	0	0			0	0	0	0	j_2
f_2	0	0			0	0	0	0	
f_1	0	0	0	0			0	0	j_3
f_2	0	0	0	0			0	1	
f_1	0	0	0	0	0	0			j_4
f_2	0	0	0	0	0	0			
	j_1		j_2		j_3		j_4		

Figure A.1: The illustration of a matching with 2 women, 2 men, and 4 jobs with full assignment. In this example the two matched vectors are (f_1, j_1, m_1, j_2) and (f_2, j_3, m_2, j_4). Note that any Pareto frontier corresponding to this matching is 4 dimensional and cannot be illustrated in one graph.

A.1 Proof of Proposition 1

Let $(f, i, m, j), (f', i', m', j') \in (F, I, M, J)$. With Assumption 1, at the stable matching, we have

$$u^f - \alpha^f_{IH} = G(F, M, R_{FIH} - \pi^i + \gamma^i_{FH} + R_{MJW} - \pi^j + \gamma^j_{MW}, v^m - \beta^m_{JW}) \quad (39)$$

$$u^{f'} - \alpha^{f'}_{IH} = G(F, M, R_{FIH} - \pi^{i'} + \gamma^{i'}_{FH} + R_{MJW} - \pi^{j'} + \gamma^{j'}_{MW}, v^{m'} - \beta^{m'}_{JW}) \quad (40)$$

$$u^{f'} - \alpha^{f'}_{IH} \geq G(F, M, R_{FIH} - \pi^i + \gamma^i_{FH} + R_{MJW} - \pi^j + \gamma^j_{MW}, v^m - \beta^m_{JW}) \quad (41)$$

$$u^f - \alpha^f_{IH} \geq G(F, M, R_{FIH} - \pi^{i'} + \gamma^{i'}_{FH} + R_{MJW} - \pi^{j'} + \gamma^{j'}_{MW}, v^{m'} - \beta^{m'}_{JW}) \quad (42)$$

By subtracting (39) from (41) and (42) from (40), we obtain

$$\alpha^{f'}_{IH} - \alpha^f_{IH} \leq \; u^{f'} - u^f \; \leq \alpha^{f'}_{IH} - \alpha^f_{IH} \Rightarrow \; u^{f'} - u^f = \alpha^{f'}_{IH} - \alpha^f_{IH} \Rightarrow \; u^{f'} - \alpha^{f'}_{IH} = u^f - \alpha^f_{IH} = U_{FIH}$$

For singles, we can show the same result by substituting G with G_0. Therefore, the difference between the utility and unobservable term is fixed for all women in the same category and we can decompose their utility into a deterministic and a stochastic part as $u_f = U_{FIH} + \alpha^f_{IH}$. Since the Pareto frontier G

is decreasing in v and increasing in $y^f + y^m$, in similar ways, we can reformulate (39) to (42) and show $v^m = V_{MJW} + \beta^m_{JW}, \pi^f = \Pi_{FIH} + \gamma^i_{FH}$, and $\pi^j = U_{MJW} + \gamma^j_{MW}$. By plugging the difference between payoffs and unobserved terms in the formulas of Assumption 1, we obtain the relationships between the deterministic utilities.

A.2 Proof of Proposition 2

We follow the proof of Theorem 4.1 of Graham (2011) and extends it in a three dimensional case. First, we show that the conditional choice probabilities are strictly increasing in the corresponding deterministic gain. Then we apply the sub-allocation feasibility condition in different 2×2 cases and show that the degree of complementarity are increasing in the conditional log odds ratios and is zero at random matching.

From the empirical matching pattern, the probability of a women f with education F has employment status I and marital status H is

$$P_{FIH} = \frac{\langle F, I, H \rangle}{\langle F, +, + \rangle}$$

Woman f chooses working status I and marital status H if and only if

$$u^f_{IH} \geq u^f_{I'H'} \quad \forall I', H'$$

From Proposition 1, we can derive the empirical choice probabilities from the model as follows

$$\begin{aligned} P_{FIH} &= \Pr\{I, H = \arg\max u^f_{KL}\} \\ &= \Pr\{\alpha^f_{KL} \leq U_{FIH} - U_{FKL} + \alpha^f_{IH}, \forall K \neq I, L \neq H\} \\ &= \int_{-\infty}^{+\infty} \prod_{KL \neq IH} F_\alpha(U_{FIH} - U_{FKL} + \alpha^f_{IH}) f_\alpha(\alpha^f_{IH}) d\alpha^f_{IH} \end{aligned} \tag{43}$$

where $F_\alpha(.)$ and $f_\alpha(.)$ are respectively the CDF and PDF of α^f_{IH}.

Following Manski (1975), for all $IH \neq I'H'$

$$\begin{aligned} P_{FIH} - P_{FI'H'} = \int_{-\infty}^{+\infty} \Bigg[&\prod_{KL \neq IH} F_\alpha(U_{FIH} - U_{FKL} + \alpha^f) \\ &- \prod_{KL \neq I'H'} F_\alpha(U_{FI'H'} - U_{FKL} + \alpha^f) \Bigg] f_\alpha(\alpha^f) d\alpha^f \end{aligned} \tag{44}$$

and because F_α is strictly increasing, this gives

$$U_{FIH} \gtreqless U_{FI'H'} \quad \Leftrightarrow \quad P_{FIH} \gtreqless P_{FI'H'} \tag{45}$$

We can extend (45) to the conditional choice probabilities $\Pr\{u^f_{I'H'} < u^f_{IH}\} = \frac{P_{FIH}}{P_{FIH} + P_{FI'H'}}$ by dividing

	IH	$I'H'$	sum
F	S_{FIH}	$S_{F+} - S_{FIH}$	S_{F+}
F'	$S_{+IH} - S_{FIH}$	$1 - S_{F+} - S_{+IH} + S_{FIH}$	$1 - S_{F+}$
sum	S_{+IH}	$1 - S_{+IH}$	1

Table A.1: 2×2 sub-allocation contingency table with rows F, F' and columns $IH, I'H'$

the right-hand side inequality to $P_{FIH} + P_{FI'H'}$ (which is positive)

$$U_{FIH} \gtreqless U_{FI'H'} \qquad \Leftrightarrow \qquad \Pr\{u^f_{I'H'} < u^f_{IH}\} \gtreqless \Pr\{u^f_{IH} < u^f_{I'H'}\} \tag{46}$$

which states that the conditional choice probabilities are strictly increasing in the corresponding deterministic gain. We use this result in below.

Let $F_{\Delta\alpha}$ be the distribution function of the difference in α, then

$$\Pr\{u^f_{I'H'} < u^f_{IH}\} = \Pr\{\alpha^f_{I'H'} - \alpha^f_{IH} < U_{FIH} - U_{FI'H'}\} = F_{\Delta\alpha}(U_{FIH} - U_{FI'H'})$$

Now, consider the 2×2 sub-allocation contingency table with rows F, F' and columns $IH, I'H'$ as shown in Table A.1, where[10]

$$S_{FIH} = \frac{\langle F, I, H\rangle}{\langle F, I, H\rangle + \langle F, I', H'\rangle + \langle F', I, H\rangle + \langle F', I', H'\rangle} \tag{47}$$

$$S_{F+} = \frac{\langle F, I, H\rangle + \langle F, I', H'\rangle}{\langle F, I, H\rangle + \langle F, I', H'\rangle + \langle F', I, H\rangle + \langle F', I', H'\rangle} \tag{48}$$

$$S_{+IH} = \frac{\langle F, I, H\rangle + \langle F', I, H\rangle}{\langle F, I, H\rangle + \langle F, I', H'\rangle + \langle F', I, H\rangle + \langle F', I', H'\rangle} \tag{49}$$

Using this table, we can compute conditional choice probabilities as follows

$$\forall f \in F, \quad \Pr\{u^f_{I'H'} < u^f_{IH}\} = F_{\Delta\alpha}(U_{FIH} - U_{FI'H'}) = \frac{S_{FIH}}{S_{F+}}$$

$$\forall f \in F', \quad \Pr\{u^f_{I'H'} < u^f_{IH}\} = F_{\Delta\alpha}(U_{F'IH} - U_{F'I'H'}) = \frac{S_{+IH} - S_{FIH}}{1 - S_{F+}}$$

The strict monotonicity of the conditional choice probabilities in (46) yields,

$$U_{FIH} - U_{FI'H'} - (U_{F'IH} - U_{F'I'H'}) = F^{-1}_{\Delta\alpha}(\frac{S_{FIH}}{S_{F+}}) - F^{-1}_{\Delta\alpha}(\frac{S_{+IH} - S_{FIH}}{1 - S_{F+}}) \tag{50}$$

Exploiting the continuous and bounded derivative property, we can show that the derivative of the right-hand side of (50) w.r.t. S_{FIH} is positive

$$\frac{1}{S_{F+}} \frac{1}{f_{\Delta\alpha}(\frac{S_{FIH}}{S_{F+}})} + \frac{1}{1 - S_{F+}} \frac{1}{f_{\Delta\alpha}(\frac{S_{+IH} - S_{FIH}}{1 - S_{F+}})} > 0$$

[10]More precise notation would be $S^{F'I'H'}_{FIH}, S^{F'I'H'}_{F+}, S^{F'I'H'}_{+IH}$, but we skip the superscripts for simplicity.

Moreover, at random matching where $S_{FIH} = S_{F+}S_{+IH}$, we have $U_{FIH} + U_{F'I'H'} - U_{FI'H'} - U_{F'IH} = 0$. Hence, being strictly increasing and crossing zero at $S_{FIH} = S_{F+}S_{+IH}$ yields

$$U_{FIH} + U_{F'I'H'} - U_{FI'H'} - U_{F'IH} \gtreqless 0 \quad \Leftrightarrow \quad S_{FIH} \gtreqless S_{F+}S_{+IH} \tag{51}$$

and because ln is a strictly increasing operator, from (47) to (49), we get

$$U_{FIH} + U_{F'I'H'} - U_{FI'H'} - U_{F'IH} \gtreqless 0 \quad \Leftrightarrow \quad \ln \frac{\langle FIH\rangle\langle F'I'H'\rangle}{\langle FI'H'\rangle\langle F'IH\rangle} \gtreqless 0 \tag{52}$$

All of the conditional returns indices are as (52).

A.3 Proof of Proposition 3

Assuming a heteroskedastic Gumdel distribution for unobservables $F(x) = e^{-e^{-\frac{x}{\sigma}}}$, (43) becomes

$$P_{FIH} = \int_{-\infty}^{+\infty} \prod_{KL \neq IH} e^{-e^{\frac{U_{FKL} - U_{FIH} - \alpha_{IH}^f}{\sigma_F}}} \frac{e^{-\frac{\alpha_{IH}^f}{\sigma_F} - e^{-\frac{\alpha_{IH}^f}{\sigma_F}}}}{\sigma_F} d\alpha_{IH}^f \tag{53}$$

Assume $\zeta_{KL} = e^{\frac{U_{FKL} - U_{FIH}}{\sigma_F}}$, and $\Phi = e^{-\frac{\alpha_{IH}^f}{\sigma_F}} \to d\Phi = -\frac{e^{-\alpha_{IH}^f}}{\sigma_F} d\alpha_{IH}^f$

$$\begin{aligned} P_{FIH} &= \int_0^{+\infty} \prod_{KL \neq IH} e^{-\Phi\ \zeta_{KL}} e^{-\Phi} d\Phi = \int_0^{+\infty} e^{-\Phi(1 + \sum_{KL \neq IH} \zeta_{KL})} d\Phi \\ &= \frac{1}{1 + \sum_{KL \neq IH} \zeta_{KL}} \end{aligned}$$

and since $\zeta_{KL} = \frac{e^{\frac{U_{FKL}}{\sigma_F}}}{e^{\frac{U_{FIH}}{\sigma_F}}}$, we get

$$P_{FIH} = \frac{e^{\frac{U_{FIH}}{\sigma_F}}}{\sum_K \sum_L e^{\frac{U_{FKL}}{\sigma_F}}} \tag{54}$$

By combining these with the conditional probabilities from the contingency table $P_{FIH} = \frac{\langle F,I,H\rangle}{\langle F,+,+\rangle}$, we have

$$U_{FIH} - U_{FI'H'} = \sigma_F \ln \frac{P_{FIH}}{P_{FI'H'}} = \sigma_F \ln \frac{\langle F\,, I\,, H\rangle}{\langle F, I', H'\rangle} \tag{55}$$

Using (55) when $\sigma_F = 1$, we can simply derive the return indices as stated in the proposition.

A.4 Proof of Proposition 4

If X is distributed by $F(x) = e^{-e^{-\frac{x-\mu}{\sigma}}}$ then $E[X] = \mu + \sigma\Upsilon$. ($\Upsilon$ is Euler's constant).

$$\Pr\{\max_{f\in F} u^f_{IH} \leq x \,|\, I \in \mathcal{I}, H \in \mathcal{H}\} = \prod_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} \Pr\{U_{FIH} + \sigma_F \alpha^f_{IH} \leq x\} = \prod_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} \exp\Big(- \exp(-\frac{x - U_{FIH}}{\sigma_F})\Big)$$

$$= \exp\Big(- \exp(-\frac{x}{\sigma_F}) \sum_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} \exp(\frac{U_{FIH}}{\sigma_F})\Big) = \exp\Big(- \exp\big(- \frac{x - \sigma_F \ln \sum_{IH} \exp(\frac{U_{FIH}}{\sigma_F})}{\sigma_F})\Big)$$

Therefore,

$$E[\max_{f\in F} u^f_{IH} \,|\, I \in \mathcal{I}, H \in \mathcal{H}] = \sigma_F \ln \sum_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} e^{\frac{U_{FIH}}{\sigma_F}} + \sigma_F \Upsilon$$

With the same logic, for any I' and H', $E[\max_{f\in F} u^f_{I'H'}] = U_{FI'H'} + \sigma_F\Upsilon$. Thus, from (54) and (55)

$$E[\max_{f\in F} u^f_{IH} \,|\, I \in \mathcal{I}, H \in \mathcal{H}] - E[\max_{f\in F} u^f_{I'H'}]$$
$$= \sigma_F \ln \sum_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} e^{\frac{U_{FIH} - U_{FI'H'}}{\sigma_F}} = \sigma_F \ln \sum_{\substack{I\in\mathcal{I}\\H\in\mathcal{H}}} \frac{\langle F, I, H\rangle}{\langle F, I', H'\rangle} = \sigma_F \ln \frac{\langle F, I \in \mathcal{I}, H \in \mathcal{H}\rangle}{\langle F, I', H'\rangle}$$

By normalizing $U_{F00} = 0$, when $\sigma_F = 1$, we have the case stated in the Proposition.

A.5 Proof of Proposition 5

The individual utilities in this ETU model are

$$u^f = \begin{cases} a^{fm} + b^{fi} + \tau^{fm} \ln \rho^{fimj} y^{fimj} & \mu(f,m) = \nu(f,i) = 1 \\ a^{fm} + \tau^{fm} \ln \rho^{f0mj} y^{fimj} & \mu(f,m) = 1,\ \sum_i \nu(f,i) = 0 \\ a^{f0} + b^{fi} + \tau^{f0} \ln y^{fi00} & \sum_m \mu(f,m) = 0,\ \nu(f,i) = 1 \\ a^{f0} & \sum_m \mu(f,m) = \sum_i \nu(f,i) = 0 \end{cases}$$

$$v^f = \begin{cases} a'^{fm} + b'^{mj} + \tau^{fm} \ln(1 - \rho^{fimj}) y^{fimj} & \mu(f,m) = \nu'(m,j) = 1 \\ a'^{fm} + \tau^{fm} \ln(1 - \rho^{f0mj}) y^{fimj} & \mu(f,m) = 1,\ \sum_i \nu'(m,j) = 0 \\ a^{0m} + b'^{mj} + \tau^{0m} \ln y^{00mj} & \sum_f \mu(f,m) = 0,\ \nu'(m,j) = 1 \\ a^{0m} & \sum_f \mu(f,m) = \sum_i \nu'(m,j) = 0 \end{cases}$$

$$\pi^i = \begin{cases} r^{ei} - y^e & \nu(e,i) = 1 \text{ or } \nu'(e,i) = 1 \\ 0 & \sum_e \nu(e,i) + \nu'(e,i) = 0 \end{cases}$$

and the Pareto frontiers becomes

$$\text{For couples: } \exp(\frac{u^f - a^{fm} - b^{fi}}{\tau^{fm}}) + \exp(\frac{v^m - a'^{fm} - b'^{mj}}{\tau^{fm}}) = r^{fi} + r^{mj} - \pi^i - \pi^j$$
$$\text{For singles: } \exp(\frac{u^f - b^{fi}}{\tau^{f0}}) = r^{fi} - \pi^i, \qquad \exp(\frac{v^m - b'^{mj}}{\tau^{0m}}) = r^{mj} - \pi^j$$

With assumption 1, the Pareto frontiers become

$$\exp(\frac{u^f - \alpha^f_{IMJ} - A_{FM} - B_{FI}}{\tau_{FM}}) + \exp(\frac{v^m - \beta^m_{FIJ} - A'_{FM} - B'_{MJ}}{\tau^{FM}}) = R^{FI} + R^{MJ} - \pi^i + \gamma^i_{FMJ} - \pi^j + \gamma^j_{FIM}$$
$$\exp(\frac{u^f - \alpha^f_{I00} - B_{FI}}{\tau_{F0}}) = R_{FI} - \pi^i + \gamma_{F00}, \qquad \exp(\frac{v^m - \beta^m_{00J} - B'_{MJ}}{\tau_{0M}}) = R_{MJ} - \pi^j + \gamma_{00M}$$

and the deterministic utilities are written as

$$\begin{aligned}
U_{FIMJ} &= A_{FM} + B_{FI} + \tau_{FM} \ln \rho_{FIMJ} Y_{FIMJ} & V_{FIMJ} &= A'_{FM} + B'_{FI} + \tau_{FM} \ln(1 - \rho_{FIMJ}) Y_{FIMJ} \\
U_{F0MJ} &= A_{FM} + \tau_{FM} \ln \rho_{F0MJ} Y_{F0MJ} & V_{F0MJ} &= A_{FM} + B'_{FI} + \tau_{FM} \ln(1 - \rho_{F0MJ}) Y_{F0MJ} \\
U_{FIM0} &= A_{FM} + B_{FI} + \tau_{FM} \ln \rho_{FIM0} Y_{FIM0} & V_{FIM0} &= A'_{FM} + \tau_{FM} \ln(1 - \rho_{FIM0}) Y_{FIM0} \\
U_{FI00} &= A_{F0} + B_{FI} + \tau_{F0} \ln Y_{FI00} & V_{00MJ} &= A'_{0M} + B'_{FI} + \tau_{0M} \ln Y_{00MJ} \\
U_{F0M0} &= A_{FM} & V_{F0M0} &= A'_{FM}
\end{aligned}$$

By combining these equation and solving for ρ_{FIMJ}, the Pareto frontier of couples become

$$\exp\left(\frac{U_{FIMJ} - U_{F0M0} - U_{FI00} + U_{F000}}{\tau_{FM}}\right) Y_{FI00}^{\frac{\tau_{F0}}{\tau_{FM}}} + \exp\left(\frac{V_{FIMJ} - V_{F0M0} - V_{00MJ} + V_{00M0}}{\tau_{FM}}\right) Y_{00MJ}^{\frac{\tau_{0M}}{\tau_{FM}}} = Y_{FIMJ}$$

and the sharing rule becomes

$$\rho_{FIMJ} = \left(1 + \exp\left(\frac{V_{FIMJ} - V_{F0M0} - V_{00MJ} + V_{00M0} - U_{FIMJ} + U_{F0M0} + U_{FI00} - U_{F000}}{\tau_{FM}}\right)\left(\frac{Y_{00MJ}^{\tau_{0M}}}{Y_{FI00}^{\tau_{F0}}}\right)^{\frac{1}{\tau_{FM}}}\right)^{-1}$$

To find the expected singlehood income, note that $\bar{U}_{F,\geq 1,00} = U_{F000} + \bar{B}_{F,\geq 1} + \tau_{F0} \ln \bar{Y}_{F,\geq 1,00}$. If we assume just-identified estimation for U and V then,

$$\bar{U}_{F,\geq 1,00} - U_{F000} = \ln \frac{\langle F, \geq 1, 0, 0 \rangle}{\langle F, 0, 0, 0 \rangle}, \qquad \bar{B}_{F+} = \ln \sum_{I=1}^{N_J} e^{B_{FI}} = \ln \sum_{I=1}^{N_J} \frac{\langle F, I, 0, 0 \rangle}{\langle F, 0, 0, 0 \rangle} Y_{FI00}^{-\tau_{F0}}$$

which yields

$$\bar{Y}_{F,\geq 1,0,0} = \left(\sum_{I=1}^{N_J} \frac{\langle F, I, 0, 0 \rangle}{\langle F, \geq 1, 0, 0 \rangle} Y_{FI00}^{-\tau_{F0}} \right)^{\frac{-1}{\tau_{F0}}} \text{ and similarly } \bar{Y}_{0,0,M,\geq 1} = \left(\sum_{J=1}^{N_J} \frac{\langle 0, 0, M, J \rangle}{\langle 0, 0, M, \geq 1 \rangle} Y_{00MJ}^{-\tau_{0M}} \right)^{\frac{-1}{\tau_{0M}}}$$

Thus, the average income of working singles equals the weighted generalized mean of income from different jobs with exponent $-\tau_{F0}$. We assume the reservation singlehood income of non-working married partners $\hat{Y}_{F000}$ and $\hat{Y}_{00M0}$ are equal to the average income of working singles.

Note that under the assumption that $\hat{Y}_{F000} = \bar{Y}_{F,\geq 1,0,0}$ and $\hat{Y}_{00M0} = \bar{Y}_{0,0,M,\geq 1}$

$$B_{F0} = \ln \frac{\langle F000\rangle}{\langle F, \geq 1, 0, 0\rangle} + \ln \sum_{I=1}^{N_J} e^{B_{FI}} = \ln \sum_{I=1}^{N_J} \frac{\langle FI00\rangle}{\langle F \geq 1\,0\,0\rangle} \frac{1}{Y_{FI00}^{\tau_{F0}}} = -\tau_{F0} \ln \bar{Y}_{F000}$$

$$B'_{M0} = \ln \frac{\langle 00M0\rangle}{\langle 0, 0, M, \geq 1\rangle} + \ln \sum_{J=1}^{N_J} e^{B'_{MJ}} = \ln \sum_{J=1}^{N_J} \frac{\langle 0, 0, M, J\rangle}{\langle 0, 0, M, \geq 1\rangle} \frac{1}{Y_{00MJ}^{\tau_{0M}}} = -\tau_{0M} \ln \bar{Y}_{00M0}$$

A.6 MDE Estimator and its Weighting Matrix

Let $\langle FIMJ\rangle$ be the population of the respective type of couples, then the vector of moment $\lambda(\theta)$ has three types of elements as follows

1. $N_E\Big((N_J+1)\big(1+N_E(N_J+1)\big)-1\Big)$ moments[11] as

$$\mathrm{PF}_{FIMJ} = U_{FIMJ} - U_{F000} - \ln \frac{\langle FIMJ\rangle}{\langle F\,0\,0\,0\rangle}$$

2. $N_E\Big((N_J+1)\big(1+N_E(N_J+1)\big)-1\Big)$ moments as

$$\mathrm{PM}_{FIMJ} = V_{FIMJ} - V_{00M0} - \ln \frac{\langle FIMJ\rangle}{\langle 0\,0\,M\,0\rangle}$$

3. $N_E^2\big((N_J+1)^2-1\big)$ moments[12] as

$$\begin{aligned}\mathrm{ETU}_{FIMJ} = \ln \Bigg(&\exp\big(\frac{U_{FIMJ} - U_{F0M0} - U_{FI00} + U_{F000}}{\tau_{FM}}\big)\, Y_{FI00}^{\frac{\tau_{F0}}{\tau_{FM}}} \\ &+ \exp\big(\frac{V_{FIMJ} - V_{F0M0} - V_{00MJ} + V_{00M0}}{\tau_{FM}}\big)\, Y_{00MJ}^{\frac{\tau_{0M}}{\tau_{FM}}}\Bigg) - \ln Y_{FIMJ}\end{aligned}$$

The number of parameters are $2N_E\Big((N_J+1)\big(1+N_E(N_J+1)\big)-1\Big) + N_E^2 + 2N_E$

In this setting, since $P_{FIH} = \frac{\langle F,I,H\rangle}{\langle F,+,+\rangle}$, the covariance of population moments becomes

$$\begin{aligned}\mathrm{Cov}(\frac{U_{FIH}}{\sigma_F}, \frac{U_{FI'H'}}{\sigma_F}) &= \mathrm{Cov}(\ln P_{FIH} - \ln P_{F00},\ \ln P_{FI'H'} - \ln P_{F00}) \\ &= \mathrm{Cov}(\ln P_{FIH}, \ln P_{FI'H'}) + \mathrm{Var}(\ln P_{F00}) - \mathrm{Cov}(\ln P_{FIH}, \ln P_{F00}) - \mathrm{Cov}(\ln P_{FI'H'}, \ln P_{F00})\end{aligned}$$

In the large markets the matching pattern of two different groups are independent and for $F_1 \neq F_2$

$$\forall\, I', H':\ \mathrm{Cov}(\ln P_{F_1IH}, \ln P_{F_2I'H'}) = 0$$

[11] $F \in \{1,\ldots,N_E\}, I \in \{0,\ldots,N_J\}, MJ \in \{0\} \cup (\{1,\ldots,N_E\} \times \{0,\ldots,N_J\})$ for each F, by benchmarking U_{F000}

[12] $F, M \in \{1,\ldots,N_E\}$ and $(I,J) \in (\{0,\ldots,N_J\} \times \{0,\ldots,N_J\}) \setminus (\{0\} \times \{0\})$, excluding $F0M0$.

From the properties of the multinomial distribution, we have

$$\mathrm{Var}(P_{FIH}) = \frac{P_{FIH}(1-P_{FIH})}{\mathcal{N}_F} \qquad \mathrm{Cov}(P_{FIH}, P_{FI'H'}) = -\frac{P_{FIH}P_{FI'H'}}{\mathcal{N}_F}$$

where $\mathcal{N}_F$ is the total population of category F in the contingency table. Using $\mathrm{Cov}\left(\ln(x), \ln(y)\right) \approx \frac{\mathrm{Cov}(x,y)}{\mathrm{E}(x)\,\mathrm{E}(y)}$, we can approximate the above elements of covariance matrix by

$$\mathrm{Cov}(\ln P_{FIH}, \ln P_{F'I'H'}) = \mathbb{1}(F'=F)\frac{\mathbb{1}(I'=I \;\&\; H'=H) - P_{FI'H'}}{\mathcal{N}_F P_{FI'H'}}$$

Therefore, for the population moments (35), we have

$$\mathrm{Cov}\left(U_{FIH}, U_{F'I'H'}\right) = \begin{cases} \frac{\sigma_F^2}{\mathcal{N}_F}(\frac{1}{P_{FIH}} + \frac{1}{P_{F00}}) & F=F', I=I', H=H' \\ \frac{\sigma_F^2}{\mathcal{N}_F P_{F00}} & F=F', I\neq I' \text{ or } H \neq H' \\ 0 & F \neq F' \end{cases}$$

For the aggregate return the standard error can be computed accordingly. For example, the conditional marriage return becomes

$$\begin{aligned} \mathrm{Var}(r^m_{F_1F_2M}) =& \,\mathrm{Cov}(\bar{U}_{F_2+M} - \bar{U}_{F_2+0} - \bar{U}_{F_1+M} + \bar{U}_{F_1+0},\ \bar{U}_{F_2+M} - \bar{U}_{F_2+0} - \bar{U}_{F_1+M} + \bar{U}_{F_1+0}) \\ =& \,\mathrm{Var}(\bar{U}_{F_2+M}) + \mathrm{Var}(\bar{U}_{F_2+0}) - 2\,\mathrm{Cov}(\bar{U}_{F_2+M}, \bar{U}_{F_2+0}) \\ &+ \mathrm{Var}(\bar{U}_{F_1+M}) + \mathrm{Var}(\bar{U}_{F_1+0}) - 2\,\mathrm{Cov}(\bar{U}_{F_1+M}, \bar{U}_{F_1+0}) \end{aligned}$$

The standard error of aggregate utilities can be computed using delta method. Any aggregate utility $\bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}}$ is a function of U_{FIMJ} with the gradient vector

$$\triangledown \bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}} = \begin{cases} \frac{\exp(\frac{U_{FIMJ}}{\sigma_F})}{\sum_{I,M,J}\exp(\frac{U_{FIMJ}}{\sigma_F})} & (I,M,J) \in (\mathcal{I},\mathcal{M},\mathcal{J}) \\ 0 & \text{Otherwise} \end{cases}$$

Then, $\mathrm{Var}(\bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}}) = (\triangledown \bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}})^T\,\mathrm{Cov}(U_{FIMJ})\,\triangledown \bar{U}_{F\mathcal{I}\mathcal{M}\mathcal{J}}$

Regarding earnings moments, we assume a diagonal covariance structure.[13] Note that for the couples that none of the partners have a job, there is no earning moment and thus their utilities are just-identified.

To find the variance of estimated parameters (and faster optimization), we also need to compute $\Lambda(\theta)$ as the derivative matrix of the vector of moment equations $\lambda(\theta)$ with respect to the vector of structural parameters θ. $\Lambda(\theta)$ is a matrix with different blocks based on the following derivatives with other elements

[13]Following Altonji and Segal (1996), the empirical literature on the minimum distance estimation use either an identity or a diagonal weighting matrix for earnings moments due to the large estimation error for the inverse sample covariance matrix.

as zero.

$$
\begin{aligned}
\frac{\partial \mathrm{PF}_{FIMJ}}{\partial U_{FIMJ}} &= \frac{\partial \mathrm{PM}_{FIMJ}}{\partial V^{FIMJ}} = 1 \\
\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial U_{FIMJ}} &= -\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial U_{F0M0}} = -\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial U_{FI00}} = \frac{\rho_{FIMJ}}{\tau_{FM}} \\
\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial V_{FIMJ}} &= -\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial V_{F0M0}} = -\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial V_{00MJ}} = \frac{1-\rho_{FIMJ}}{\tau_{FM}} \\
\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial \tau_{F0}} &= \frac{\rho_{FIMJ}}{\tau_{FM}} \ln Y_{FI00} \qquad \frac{\partial \mathrm{ETU}_{F0MJ}}{\partial \tau_{F0}} = \frac{\rho_{F0MJ}}{\tau_{FM}} \frac{\sum_{J=1}^{N_J} \langle FI00\rangle Y_{FI00}^{-\tau_{F0}} \ln Y_{FI00}}{\sum_{J=1}^{N_J} \langle FI00\rangle Y_{FI00}^{-\tau_{F0}}} \\
\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial \tau_{0M}} &= \frac{1-\rho_{FIMJ}}{\tau_{FM}} \ln Y_{00MJ} \qquad \frac{\partial \mathrm{ETU}_{FIM0}}{\partial \tau_{0M}} = \frac{1-\rho_{FIM0}}{\tau_{FM}} \frac{\sum_{J=1}^{N_J} \langle 00MJ\rangle Y_{00MJ}^{-\tau_{0M}} \ln Y_{00MJ}}{\sum_{J=1}^{N_J} \langle 00MJ\rangle Y_{00MJ}^{-\tau_{0M}}} \\
\frac{\partial \mathrm{ETU}_{FIMJ}}{\partial \tau_{FM}} &= \frac{-1}{\tau_{FM}^2} \Big(\rho_{FIMJ}(U_{FIMJ} - U_{F0M0} - U_{FI00} + U_{F000} + \tau_{F0} \ln Y_{FI00}) \\
&\qquad + (1-\rho_{FIMJ})(V^{FIMJ} - V^{F0M0} - V_{00MJ} + V_{00M0} + \tau_{0M} \ln Y_{00MJ}) \Big)
\end{aligned}
$$

A.7 The just-identified world

One way to estimate the model is using just-identified estimation of U_{FIMJ} and V_{FIMJ}, and then get an estimation for τ. In practice, when the population sample is large, the weight of population moments becomes larger than earnings moments in the efficient MDE estimator. This means that the estimated parameters for U and V are close to their just-identified counterparts. More importantly, if we plug just-identified parameters in the model it gives good insight in terms of link between population and earnings.

$$
\Big(\frac{\langle FIMJ\rangle\langle F000\rangle}{\langle F0M0\rangle\langle FI00\rangle}\Big)^{\frac{1}{\tau_{FM}}} Y_{FI00}^{\frac{\tau_{F0}}{\tau_{FM}}} + \Big(\frac{\langle FIMJ\rangle\langle 00M0\rangle}{\langle F0M0\rangle\langle 00MJ\rangle}\Big)^{\frac{1}{\tau_{FM}}} Y_{00MJ}^{\frac{\tau_{0M}}{\tau_{FM}}} = Y_{FIMJ} \tag{56}
$$

$$
\rho_{FIMJ} = \left(1 + \Big(\frac{\langle FI00\rangle\langle 00M0\rangle}{\langle F000\rangle\langle 00MJ\rangle} \frac{Y_{00MJ}^{\tau_{0M}}}{Y_{FI00}^{\tau_{F0}}}\Big)^{\frac{1}{\tau_{FM}}}\right)^{-1} \tag{57}
$$

B Additional Tables and Figures

Table A.2: Sample number of households with a women between 30 and 60 or a man between 32 and 62 across the U.S. datasets.

year	data	IPUMS sample	number
1960	Census	us1960b	2,111,145
1970	Census	us1970a	441,395
1980	Census	us1980a	2,593,674
1990	Census	us1990a	3,215,513
2000	Census	us2000a	4,001,166
2007	ACS 5-years	us2009e	4,350,416
2012	ACS 5-years	us2014c	4,512,218
2017	ACS 5-years	us2019c	4,506,384

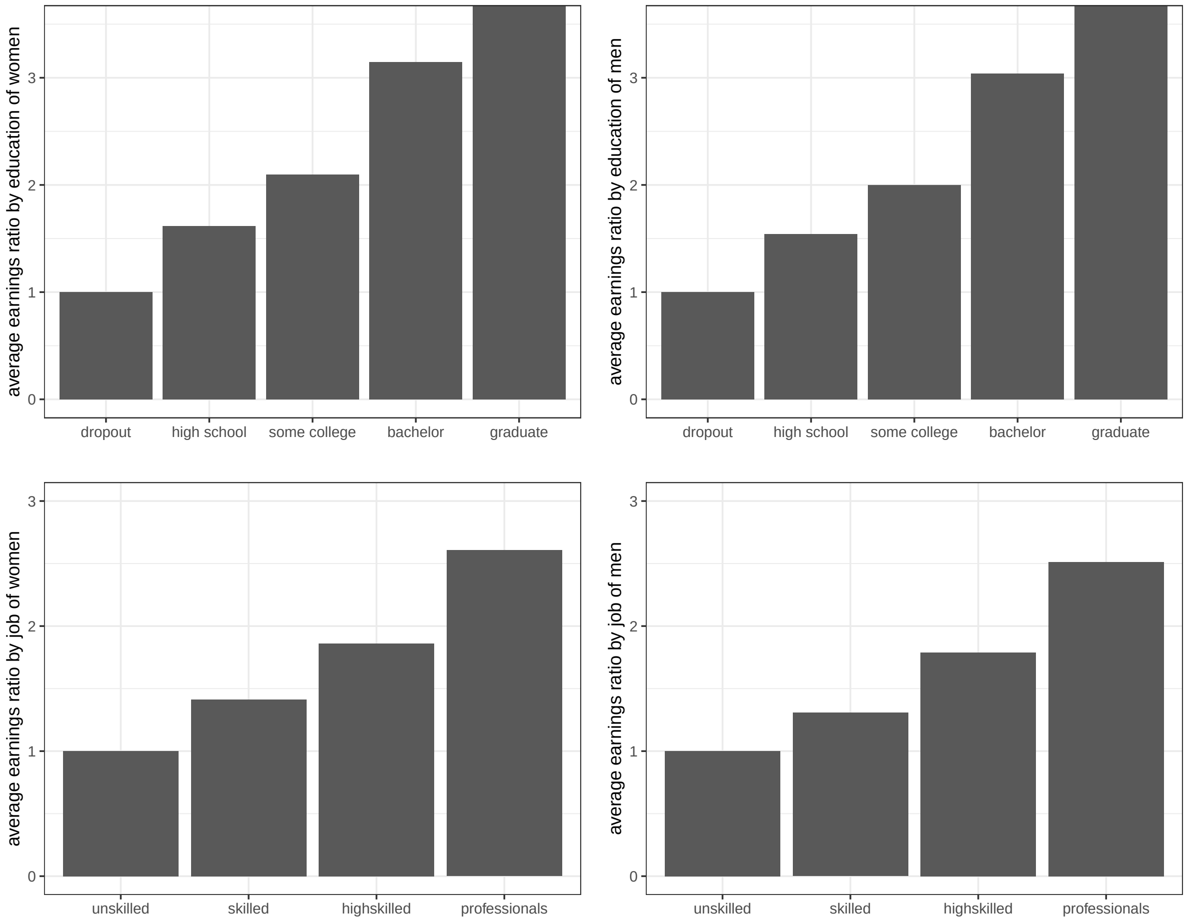

Figure A.2: Average earnings ratio to the lowest rank by education and job classifications

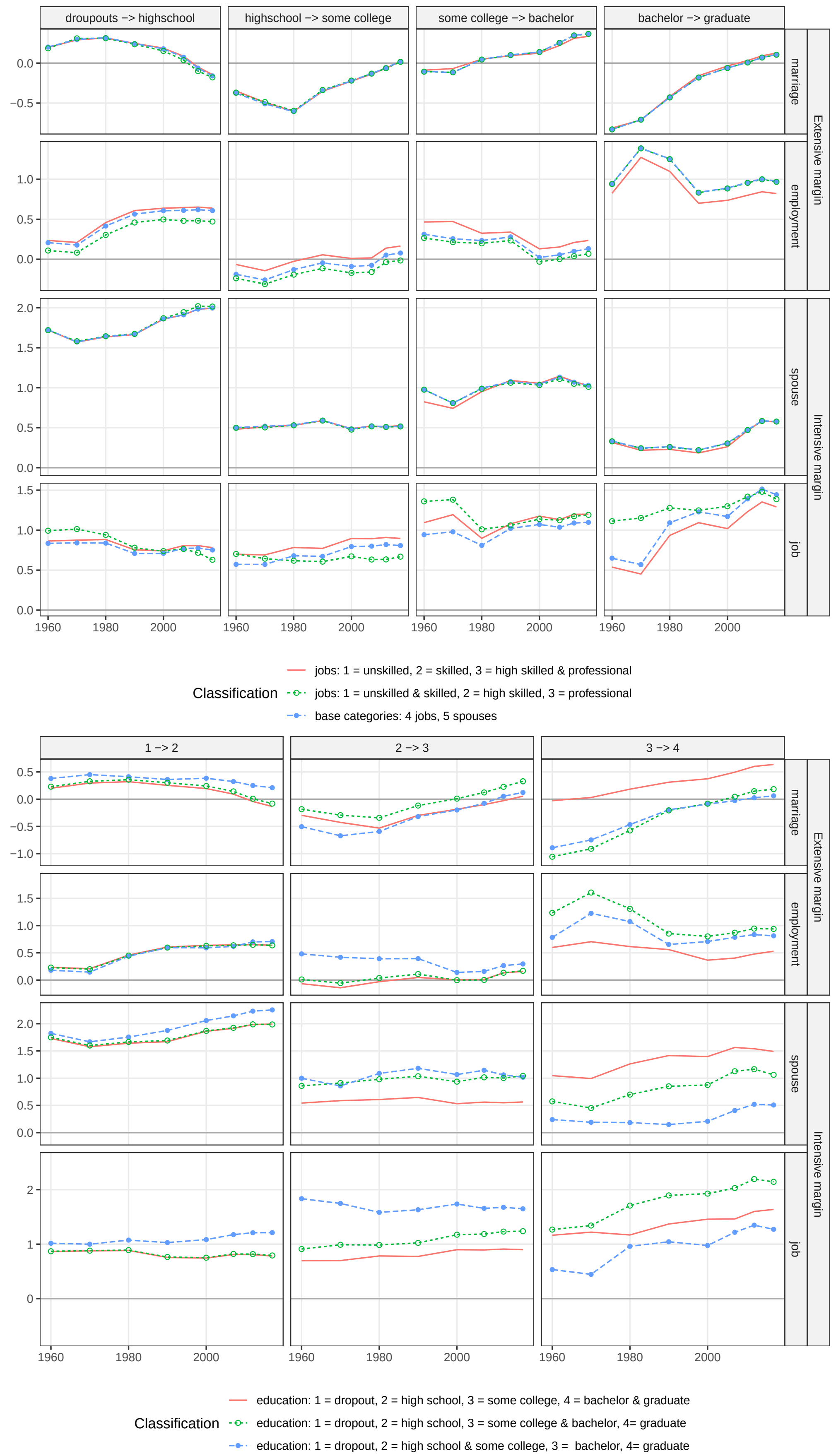

Figure A.3: The aggregate returns for different classifications of education and occupation. For illustration only the returns of women are reported. For men similar results hold.

Table A.3: Estimation of transferability terms τ_{FM} for different educational categories. The rows and columns show women's and men's education, respectively.

year	women	τ_{FM}					
			D	HS	SC	BA	G
1960			24.34 (9.04)	22.75 (7.92)	23.17 (8.47)	22.82 (8.15)	23.74 (8.99)
	D	20.05 (6.58)	23.25 (8.11)	22.22 (7.36)	22.66 (7.89)	22.44 (7.7)	23.06 (8.33)
	HS	21.38 (6.65)	23.28 (8.02)	22.44 (7.41)	22.81 (7.82)	22.55 (7.64)	23.14 (8.22)
	SC	21.17 (6.62)	23.25 (8.03)	22.45 (7.41)	22.62 (7.76)	22.43 (7.58)	22.93 (8.09)
	BA	21.25 (6.54)	23.01 (7.88)	22.27 (7.27)	22.64 (7.68)	22.29 (7.48)	22.7 (7.88)
	G	21.95 (7.21)	23.17 (8.01)	22.58 (7.48)	22.69 (7.71)	22.63 (7.62)	22.95 (8.04)
1970			24.02 (11.44)	23.55 (10.91)	24.64 (11.86)	23.07 (10.46)	23.53 (10.9)
	D	24.01 (11.33)	24.16 (11.39)	23.75 (10.98)	24.56 (11.7)	23.39 (10.69)	23.87 (11.12)
	HS	22.67 (9.8)	23.62 (10.75)	23.39 (10.54)	24.14 (11.24)	22.93 (10.19)	23.39 (10.63)
	SC	23.2 (10.44)	23.81 (10.99)	23.65 (10.81)	24.19 (11.31)	23.02 (10.33)	23.26 (10.56)
	BA	22.73 (10.08)	23.47 (10.68)	23.46 (10.61)	24.2 (11.29)	23.05 (10.33)	23.03 (10.36)
	G	23.31 (10.58)	23.82 (11.05)	23.51 (10.69)	24.02 (11.16)	23.36 (10.54)	23.54 (10.72)
1980			34.62 (21.62)	34.49 (21.12)	35.01 (21.72)	35.63 (22.59)	35.22 (22.07)
	D	34.57 (21.27)	34.76 (21.56)	34.7 (21.27)	35.13 (21.8)	35.52 (22.42)	35.41 (22.26)
	HS	34.29 (20.59)	34.64 (21.21)	34.62 (21.03)	34.88 (21.37)	35.26 (21.96)	35.05 (21.7)
	SC	34.16 (20.51)	34.64 (21.24)	34.64 (21.06)	34.81 (21.3)	35.2 (21.9)	34.93 (21.55)
	BA	33.33 (19.47)	34.42 (20.99)	34.27 (20.64)	34.62 (21.06)	35.04 (21.69)	34.69 (21.25)
	G	34.56 (21.18)	35.07 (21.88)	35.02 (21.64)	35.04 (21.65)	35.23 (22)	35.24 (21.99)
1990			22.79 (12.62)	22.64 (12.31)	22.85 (12.47)	23.18 (12.94)	23.23 (13.05)
	D	23.15 (13.01)	22.97 (12.76)	22.88 (12.57)	22.99 (12.66)	23.26 (13.04)	23.48 (13.33)
	HS	22.12 (11.67)	22.55 (12.17)	22.5 (12.03)	22.62 (12.14)	22.87 (12.53)	23.07 (12.8)
	SC	21.92 (11.41)	22.45 (12.04)	22.46 (11.95)	22.53 (12.01)	22.76 (12.38)	22.86 (12.54)
	BA	21.97 (11.46)	22.56 (12.13)	22.52 (12)	22.64 (12.09)	22.76 (12.35)	22.83 (12.48)
	G	22.37 (11.97)	22.89 (12.55)	22.78 (12.34)	22.8 (12.34)	22.79 (12.43)	22.8 (12.5)
2000			22.5 (14.58)	23.01 (15.26)	22.9 (14.98)	23.27 (15.55)	23.08 (15.39)
	D	22.97 (15.18)	22.74 (14.88)	23.07 (15.29)	23.01 (15.14)	23.44 (15.77)	23.27 (15.64)
	HS	22.59 (14.56)	22.57 (14.56)	22.81 (14.88)	22.77 (14.75)	23.05 (15.22)	23.08 (15.32)
	SC	22.22 (14.07)	22.4 (14.33)	22.7 (14.7)	22.64 (14.56)	22.85 (14.95)	22.77 (14.92)
	BA	21.94 (13.72)	22.28 (14.18)	22.56 (14.51)	22.47 (14.33)	22.65 (14.68)	22.48 (14.54)
	G	22.66 (14.77)	23.02 (15.21)	23.08 (15.26)	22.93 (15)	22.82 (14.95)	23 (15.26)
2007			23.4 (15.71)	22.98 (14.95)	22.86 (14.77)	22.89 (14.82)	23.15 (15.26)
	D	23.22 (15.29)	23.34 (15.54)	23.14 (15.16)	23.04 (15)	23.21 (15.24)	23.51 (15.74)
	HS	22.75 (14.63)	23.1 (15.19)	22.81 (14.68)	22.75 (14.6)	22.8 (14.7)	23.22 (15.34)
	SC	22.41 (14.17)	22.93 (14.93)	22.66 (14.46)	22.63 (14.41)	22.61 (14.43)	22.96 (14.99)
	BA	22.1 (13.74)	22.73 (14.64)	22.54 (14.27)	22.47 (14.17)	22.38 (14.12)	22.57 (14.49)
	G	22.16 (13.95)	22.72 (14.72)	22.59 (14.44)	22.49 (14.3)	22.39 (14.23)	22.48 (14.41)
2012			23.23 (15.71)	23.15 (15.51)	22.99 (15.22)	23.07 (15.36)	23.16 (15.53)
	D	22.68 (14.82)	22.95 (15.25)	22.95 (15.22)	22.88 (15.07)	23.15 (15.46)	23.31 (15.71)
	HS	22.76 (14.91)	22.93 (15.2)	22.83 (15)	22.75 (14.86)	22.85 (15.05)	23.1 (15.43)
	SC	22.61 (14.73)	22.88 (15.12)	22.77 (14.91)	22.67 (14.75)	22.76 (14.92)	22.9 (15.17)
	BA	22.47 (14.48)	22.85 (15.04)	22.71 (14.79)	22.58 (14.59)	22.6 (14.7)	22.57 (14.72)
	G	22.19 (14.15)	22.71 (14.85)	22.64 (14.74)	22.53 (14.55)	22.44 (14.5)	22.44 (14.57)
2017			23.14 (17.35)	22.9 (16.81)	22.9 (16.77)	22.98 (16.99)	23.34 (17.57)
	D	23.07 (17.07)	23.09 (17.16)	22.92 (16.83)	22.93 (16.83)	23.03 (17.05)	23.48 (17.75)
	HS	22.92 (16.84)	22.94 (16.95)	22.77 (16.58)	22.77 (16.57)	22.92 (16.87)	23.24 (17.4)
	SC	22.48 (16.19)	22.77 (16.67)	22.57 (16.25)	22.59 (16.28)	22.71 (16.53)	23.1 (17.17)
	BA	22.31 (15.87)	22.65 (16.41)	22.52 (16.14)	22.49 (16.09)	22.45 (16.13)	22.73 (16.61)
	G	22.39 (16.07)	22.77 (16.67)	22.67 (16.42)	22.56 (16.25)	22.34 (16.01)	22.6 (16.44)

Table A.4: Estimation of transferability terms τ_{FM} for different educational categories. The rows and columns show women's and men's education, respectively.

year	homoskedastic τ	(95% CI)
1960	32.27	(8.69, 119.87)
1970	80.6	(3.61, 1798.88)
1980	42.56	(6.12, 295.94)
1990	21.14	(6.36, 70.32)
2000	23.31	(4.99, 108.76)
2007	25.33	(4.82, 133.26)
2012	22.52	(5.01, 101.25)
2017	22.82	(4.57, 114.07)

Table A.5: Estimation of sharing $r\bar{h}o_{FM}$ for different educational categories. The rows and columns show women's and men's education, respectively.

year	women	ρ_{FM}				
		D	HS	SC	BA	G
1960	D	0.183	0.165	0.137	0.136	0.115
	HS	0.328	0.316	0.267	0.267	0.227
	SC	0.311	0.298	0.249	0.249	0.210
	BA	0.350	0.340	0.288	0.287	0.242
	G	0.450	0.447	0.387	0.388	0.333
1970	D	0.406	0.358	0.274	0.353	0.307
	HS	0.373	0.326	0.247	0.320	0.277
	SC	0.428	0.380	0.291	0.374	0.324
	BA	0.423	0.375	0.287	0.370	0.319
	G	0.483	0.434	0.338	0.430	0.378
1980	D	0.402	0.339	0.303	0.258	0.285
	HS	0.462	0.395	0.355	0.304	0.334
	SC	0.460	0.393	0.353	0.302	0.332
	BA	0.423	0.357	0.319	0.272	0.299
	G	0.512	0.445	0.403	0.348	0.380
1990	D	0.463	0.406	0.359	0.301	0.285
	HS	0.438	0.381	0.335	0.278	0.262
	SC	0.441	0.384	0.337	0.280	0.263
	BA	0.497	0.439	0.389	0.326	0.307
	G	0.552	0.494	0.443	0.377	0.356
2000	D	0.498	0.383	0.363	0.298	0.307
	HS	0.519	0.402	0.382	0.312	0.323
	SC	0.509	0.392	0.371	0.302	0.312
	BA	0.522	0.403	0.382	0.311	0.321
	G	0.607	0.493	0.472	0.394	0.405
2007	D	0.421	0.400	0.376	0.335	0.296
	HS	0.443	0.421	0.396	0.353	0.312
	SC	0.436	0.414	0.389	0.345	0.305
	BA	0.457	0.435	0.409	0.364	0.321
	G	0.481	0.460	0.434	0.388	0.342
2012	D	0.395	0.339	0.322	0.273	0.256
	HS	0.473	0.413	0.394	0.337	0.316
	SC	0.481	0.421	0.402	0.344	0.322
	BA	0.527	0.466	0.447	0.385	0.360
	G	0.528	0.467	0.448	0.386	0.361
2017	D	0.443	0.415	0.383	0.331	0.275
	HS	0.479	0.451	0.417	0.363	0.302
	SC	0.452	0.423	0.390	0.337	0.279
	BA	0.496	0.467	0.433	0.376	0.312
	G	0.540	0.512	0.478	0.419	0.351

Table A.6: Matching tables over the years

matching table in 1960 : total households = 1,936,578

women's education	women's job	men's education: N.A.	D					HS					SC					BA					G				
	men's job	N.A.	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P
N.A.	N.A.		26963	44784	65956	6467	14032	3564	7254	19830	3869	6206	1598	1855	7573	2256	4460	624	333	2327	1006	4629	448	154	1066	596	6914
D	N.A.	63539	13236	74303	133106	17420	50460	674	6291	18915	4367	8842	345	1278	5048	1741	4610	88	147	778	376	2222	56	34	280	124	1610
D	U	31008	1522	27135	31353	3807	4661	78	2286	4495	885	924	40	457	951	296	400	7	44	121	41	159	1	18	50	16	102
D	S	89046	3757	54401	97116	12080	23546	259	6284	18588	3990	5533	121	1301	5163	1607	3016	26	135	689	299	1397	12	50	228	114	897
D	H	13915	617	6484	11703	2132	3682	60	769	2402	634	1091	45	201	886	361	688	7	22	147	60	412	3	5	66	28	336
D	P	6669	333	1759	4083	659	4991	41	243	950	220	955	18	76	328	130	512	5	7	57	26	246	2	5	24	15	167
HS	N.A.	12922	1205	12080	30321	5368	15747	977	6917	27235	7731	18954	333	1195	8005	3326	9849	152	163	2269	1169	7794	97	56	790	428	6239
HS	U	5671	122	4056	6054	817	1099	44	1573	3320	720	893	15	219	711	220	350	4	36	126	51	205	2	7	38	23	155
HS	S	38462	677	15508	36773	5705	9923	307	8549	31378	7675	12601	148	1641	9122	3437	7034	39	196	2070	1045	4803	32	63	602	375	3378
HS	H	17559	213	3697	9969	1977	3660	118	2375	10035	3088	5358	47	568	3572	1549	3415	17	72	1049	603	2938	23	30	346	236	2239
HS	P	6258	111	891	2429	531	2076	63	534	2284	723	2403	35	145	895	371	1346	14	21	266	165	884	13	13	71	61	799
SC	N.A.	5125	337	1674	5029	1025	4424	149	812	4208	1415	4529	351	546	4138	1879	7060	111	101	1972	1025	6796	91	38	838	422	7717
SC	U	1225	20	452	652	74	176	7	143	300	75	118	8	103	217	75	152		10	60	27	133		5	23	11	129
SC	S	10689	148	2137	5552	967	2250	53	1015	4303	1111	2465	104	580	3713	1408	3485	46	104	1191	568	2859	27	37	442	274	2829
SC	H	8236	67	851	2516	533	1130	31	512	2362	846	1577	54	348	2275	1081	2689	21	45	891	477	2344	23	28	332	256	2614
SC	P	6544	127	792	2269	475	1940	42	404	1692	464	1644	58	198	1381	514	2128	10	39	446	275	1710	16	15	204	156	2035
BA	N.A.	1694	78	146	533	156	550	57	120	639	237	983	75	81	766	457	1715	131	67	1127	670	4300	61	25	463	290	5457
BA	U	233	2	38	49	8	13	1	15	27	7	12	1	6	20	10	23	1	9	31	13	60	1	1	11	8	64
BA	S	1925	25	140	428	64	197	7	87	442	137	332	17	52	426	194	529	14	31	534	250	1230	9	14	206	110	1320
BA	H	2219	12	78	222	56	131	7	66	328	123	280	7	25	330	189	497	14	25	416	247	1142	8	9	155	115	1477
BA	P	8764	116	700	1719	348	1137	43	401	1767	518	1385	62	225	1500	641	1950	41	85	1235	679	3951	32	32	495	351	5225
G	N.A.	698	40	42	108	22	98	15	25	104	43	138	17	16	135	61	269	13	5	123	71	486	66	12	159	95	1957
G	U	87	1	15	10	3	4		2	6	2	2		2	8	2	3			3	3	11	1	4	4	2	25
G	S	663	3	25	86	16	49	3	14	52	16	51	7	8	75	38	86	2	4	47	13	121	6	5	74	33	433
G	H	857	1	14	44	15	27	1	18	60	22	54	4	7	50	35	107	1	1	43	31	114	4	2	57	47	461
G	P	9698	45	262	669	144	423	18	146	598	169	484	32	107	679	284	811	17	33	331	207	1153	37	20	373	242	4654

matching table in 1970 : total households = 418,479

women's education	women's job	men's education: N.A.	D					HS					SC					BA					G				
	men's job	N.A.	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P
N.A.	N.A.		4791	8667	12134	1528	2073	901	2358	5419	1498	1855	290	525	1760	909	1425	121	111	442	412	1512	74	98	231	198	2272
D	N.A.	11157	1709	8351	18821	2870	4551	138	1180	3918	1164	1469	44	168	767	390	734	14	24	98	67	404	8	17	48	37	283
D	U	8077	404	4055	5724	759	627	31	460	956	239	226	10	86	191	76	86	6	13	30	14	32	1	4	12	5	26
D	S	17138	858	7624	18808	2994	3167	81	1433	4701	1413	1401	33	247	997	457	705	8	27	102	88	302	2	17	49	31	226
D	H	3166	125	1150	2813	619	793	16	234	829	281	372	4	37	190	132	243	1	6	18	27	115	1	3	11	12	99
D	P	1207	65	330	952	184	538	8	78	255	101	206	4	16	93	45	98		2	9	8	68	2	2	6	4	39
HS	N.A.	3334	226	1977	5745	1137	2144	137	1652	6645	2584	4594	69	216	1392	1074	2471	22	41	285	443	2237	17	11	115	105	1778
HS	U	2095	58	738	1401	207	202	17	406	996	274	317	6	58	208	78	148		11	31	23	62		5	5	5	55
HS	S	11479	212	3214	8706	1617	1965	81	2433	9478	3139	3956	35	365	2062	1339	2370	11	59	313	324	1429	7	25	114	89	1021
HS	H	5795	76	920	2980	745	1031	39	878	4033	1699	2352	13	155	1052	870	1577	4	18	158	278	1121	5	12	70	86	933
HS	P	1778	25	244	741	150	417	12	220	920	370	807	11	45	269	172	461	5	11	45	48	302	5	4	14	26	238
SC	N.A.	955	47	318	706	153	452	21	175	736	311	859	37	83	558	492	1457	13	32	195	338	1840	21	16	91	124	2169
SC	U	310	7	83	126	20	37	1	36	94	24	38	1	14	59	18	39		4	7	7	22			5	2	42
SC	S	2758	33	417	955	207	314	16	305	1055	378	624	13	124	790	503	965	5	24	175	228	881	9	15	80	76	966
SC	H	2567	28	192	613	151	255	12	184	739	361	557	16	96	569	500	967	5	12	133	218	888	5	12	54	101	1154
SC	P	1403	20	118	327	70	220	6	82	363	154	415	9	49	258	184	523	5	8	71	91	501	1	5	29	48	637
BA	N.A.	340	13	63	86	23	64	7	38	107	58	176	13	20	82	92	272	13	11	108	226	1160	9	15	52	82	1519
BA	U	41	1	7	7		2	1	3	8	1	5			5		10	1	1	3	5	12		1	1		19
BA	S	491	10	53	82	25	33	3	27	91	42	66	4	14	51	73	111	3	7	71	85	295	1	4	25	18	376
BA	H	537	6	19	46	16	34	3	17	72	32	74		8	56	56	115		3	40	73	309	5	3	18	37	472
BA	P	2008	20	113	354	81	195	15	95	470	191	379	13	64	376	250	612	5	17	207	323	1595	10	15	100	138	2318
G	N.A.	105	11	22	30	5	11	2	9	24	13	20	4	8	17	22	47		5	6	16	113	2	5	20	22	520
G	U	20		1	6	3	2		3			1			1	1	3		1	1		5			3	1	9
G	S	219	5	22	23	6	11		9	17	5	18	2		28	12	18		4	4	12	53	1	3	19	7	138
G	H	184	1	4	10	5	7	1	6	8	5	10		2	15	6	15			1	6	30	1	2	10	14	147
G	P	2780	11	70	159	36	81	10	54	228	110	171	7	34	177	138	296	9	9	76	116	530	7	15	76	118	2308

matching table in 1980 : total households = 2,393,510

women's education	women's job	men's education N.A.	D N.A.	D U	D S	D H	D P	HS N.A.	HS U	HS S	HS H	HS P	SC N.A.	SC U	SC S	SC H	SC P	BA N.A.	BA U	BA S	BA H	BA P	G N.A.	G U	G S	G H	G P
N.A.	N.A.		29932	26953	51079	9382	6754	10477	15264	47030	13737	11456	4452	5447	23043	12013	14799	1542	1212	6367	5964	15425	1433	853	4661	4219	27576
D	N.A.	64089	19834	24012	61529	11921	9248	2712	5517	21239	6452	4992	869	1087	4872	2427	2673	194	111	571	541	1391	154	94	385	235	1398
D	U	30086	3430	10248	17299	2990	1567	419	2049	5236	1398	762	118	435	1289	526	411	16	48	134	73	154	17	46	99	49	146
D	S	57102	7064	16928	47574	9038	5888	1163	4738	19093	5375	3670	395	1064	5103	2410	2346	62	98	534	424	922	69	95	290	189	844
D	H	14815	1787	3601	10159	2728	1987	343	1105	4632	1647	1311	119	268	1316	799	866	25	25	162	184	423	14	13	93	87	375
D	P	5901	700	1109	3320	804	1878	157	371	1492	510	912	54	90	540	274	511	10	19	82	68	221	13	13	32	42	266
HS	N.A.	27606	4530	7634	26536	5670	5561	4345	10196	48784	17456	18718	1405	1976	11987	8184	11516	488	301	2273	3369	10105	330	126	990	1246	8593
HS	U	14755	785	2978	6307	1135	701	451	3100	8447	2350	1635	105	540	1961	880	928	20	64	263	204	512	19	25	100	66	362
HS	S	71625	3195	9850	31977	6319	4731	2519	13308	59248	18991	16480	723	2837	16346	9455	11270	220	350	2600	3054	7356	112	139	1021	984	5798
HS	H	44394	1520	4072	14750	3704	3075	1415	6263	31653	12874	12240	432	1466	9020	6891	8654	146	207	1584	2546	6384	84	71	695	933	5307
HS	P	14551	565	1145	4146	1001	1790	591	1729	8396	3336	5505	197	419	2659	1784	3234	79	72	512	713	2141	41	26	231	265	1751
SC	N.A.	9833	808	951	3480	837	1196	624	1242	6374	2387	3316	916	970	6848	4841	8085	364	173	2087	3340	10089	298	100	1349	1675	13950
SC	U	3385	83	347	705	145	88	38	274	895	205	203	36	264	815	342	415	7	58	124	143	307	3	28	60	66	344
SC	S	28513	553	1490	5105	980	933	399	1913	9337	2855	2992	446	1704	10263	5843	7430	113	264	2306	2456	6606	102	134	1240	1230	8172
SC	H	30969	472	1149	4210	1148	996	399	1648	8473	3201	3277	486	1442	8654	6801	8481	133	219	2020	3162	7772	117	107	1129	1686	9815
SC	P	16115	230	539	1720	437	683	188	645	3236	1259	2005	226	546	3554	2512	4789	82	114	895	1334	4301	70	68	597	757	5798
BA	N.A.	2647	152	128	450	120	171	135	166	1009	378	667	193	119	962	885	1641	240	129	1266	2101	6734	201	64	817	1187	11433
BA	U	513	13	33	57	8	6	6	26	82	23	24	1	34	85	42	64	1	20	57	52	126	3	10	38	27	166
BA	S	5552	40	150	402	88	108	50	188	937	284	368	56	188	1186	647	1107	39	129	1047	1144	3054	50	57	573	618	4557
BA	H	6813	45	83	290	100	93	47	155	784	368	428	47	165	1000	818	1114	57	86	843	1435	3196	51	40	475	776	4840
BA	P	16266	193	342	1105	272	417	172	602	2968	1146	1593	158	466	2841	2121	3455	137	224	2025	3104	10426	100	97	1198	1476	14735
G	N.A.	1603	118	128	270	63	67	63	69	256	112	150	57	47	272	202	415	54	29	189	324	998	173	58	416	539	5399
G	U	329	7	34	55	13	9	3	6	23	5	11	2	13	23	14	16	1	7	4	7	24	5	15	27	22	115
G	S	3287	35	80	190	49	46	18	58	237	81	97	19	53	346	173	267	20	24	192	198	541	22	64	390	346	2449
G	H	3669	20	30	103	24	33	15	42	191	96	95	20	53	291	211	338	16	19	149	260	590	27	54	269	470	2859
G	P	28720	193	271	891	235	325	174	473	2235	868	1069	199	450	2632	1897	2776	116	150	1354	2021	5994	256	180	1733	2521	28415

matching table in 1990 : total households = 2,886,553

women's education	women's job	men's education N.A.	D N.A.	D U	D S	D H	D P	HS N.A.	HS U	HS S	HS H	HS P	SC N.A.	SC U	SC S	SC H	SC P	BA N.A.	BA U	BA S	BA H	BA P	G N.A.	G U	G S	G H	G P
N.A.	N.A.		32018	26594	50460	8604	5343	14960	25768	67025	16192	11797	8537	13972	50300	21501	23003	2694	2843	14677	11853	31355	1409	760	4012	4056	29584
D	N.A.	55946	17486	15000	35081	6007	4240	3492	4671	14875	3709	2707	1532	1380	5550	2331	2406	277	127	665	436	1257	152	63	238	141	847
D	U	25545	3035	8280	13969	2199	1041	599	2486	5682	1257	696	209	785	2128	798	583	33	63	208	122	236	21	50	79	41	126
D	S	48818	6016	13256	36276	6082	3428	1519	5288	18393	4142	2736	672	1872	7849	2946	2775	99	192	892	585	1330	50	55	289	188	776
D	H	13049	1757	3116	8359	1965	1249	491	1478	4861	1387	1100	247	517	2326	1104	1103	38	49	262	238	517	14	26	98	81	323
D	P	4558	580	892	2621	558	1189	178	445	1601	483	716	83	192	865	436	663	13	27	143	107	289	15	9	42	34	225
HS	N.A.	28629	5107	4901	14813	2603	2522	5172	8372	32121	8662	8792	2054	2500	12745	6125	8286	647	308	2175	2226	7142	309	75	552	608	4174
HS	U	20182	1152	3001	6610	973	617	795	5007	12556	2745	1853	239	1400	4474	1612	1546	29	165	546	350	810	19	53	136	72	339
HS	S	82093	4022	9232	28722	4890	3443	3693	17953	67745	16362	13651	1411	5894	28346	12546	14040	351	630	4328	3525	9285	133	117	918	800	4456
HS	H	41203	1800	3713	12308	2480	1988	1838	8352	34032	10089	9270	785	2851	14818	8216	9666	215	344	2567	2775	7013	82	77	450	632	3835
HS	P	17195	795	1468	4498	900	1468	857	3226	12836	3840	5824	351	1159	6262	3270	5396	112	173	1111	1125	3627	35	42	237	307	2096
SC	N.A.	14043	1125	1000	3026	601	625	1021	1551	6426	1768	2227	1527	1773	9194	4682	7273	599	277	2462	2992	9966	337	68	639	1019	8798
SC	U	8245	226	659	1325	230	134	119	910	2483	574	455	136	989	2933	1043	1107	24	142	397	304	854	8	31	97	74	484
SC	S	60537	1131	2849	8882	1636	1245	950	5502	21651	5092	4822	1182	5856	29348	12717	15285	342	721	5654	5192	14014	166	106	1170	1270	9101
SC	H	51423	870	1984	6527	1392	1141	808	4351	17730	5063	4992	1025	4428	22921	12946	15425	289	581	4672	5480	14610	157	113	984	1482	10234
SC	P	32373	502	1031	3305	710	933	544	2266	9355	2696	3554	651	2447	12930	6787	11254	192	347	3006	3281	10961	118	69	674	978	8067
BA	N.A.	3555	143	126	318	90	119	170	232	879	260	424	249	244	1316	870	1574	397	178	1863	2391	7448	285	59	633	1019	10247
BA	U	1212	21	63	118	21	17	14	105	183	60	51	11	112	255	109	146	9	68	198	143	382	9	23	53	56	317
BA	S	13885	77	222	690	156	147	99	511	2298	690	734	130	660	3788	1793	2562	168	389	3257	2779	7742	87	73	840	944	7501
BA	H	13604	76	163	552	138	139	102	416	1899	714	749	141	583	3157	1973	2655	131	264	2605	3351	7668	80	58	599	1043	7605
BA	P	38104	245	500	1563	350	487	330	1508	5880	1800	2369	463	1752	9747	5097	8278	428	776	6688	7676	27699	278	170	1714	2590	27076
G	N.A.	1493	96	53	162	40	42	69	79	295	119	116	109	60	341	201	340	102	26	273	349	1132	193	27	245	348	3685
G	U	375	8	22	50	11	5	4	19	66	14	12	2	17	41	17	27	7	6	24	21	43	3	13	33	17	101
G	S	3821	46	92	264	57	47	41	139	567	164	144	38	136	677	331	428	26	36	433	342	1086	40	44	394	332	2435
G	H	4054	35	77	224	56	37	33	126	525	174	164	37	107	572	378	413	32	35	341	463	1095	41	30	251	489	2677
G	P	36985	197	280	896	228	290	269	742	2956	900	1189	397	850	4911	3030	4379	355	394	3502	4163	14023	441	162	1832	2878	37000

matching table in 2000 : total households = 3,669,215

women's education	women's job	men's education N.A.	D N.A.	D U	D S	D H	D P	HS N.A.	HS U	HS S	HS H	HS P	SC N.A.	SC U	SC S	SC H	SC P	BA N.A.	BA U	BA S	BA H	BA P	G N.A.	G U	G S	G H	G P
N.A.	N.A.		47595	39535	69746	12339	5854	34083	45325	113586	26343	14780	19518	22451	85235	35629	30154	5677	4293	23080	17659	43766	2907	1120	6005	5002	38793
D	N.A.	56636	14470	13068	29279	5019	2592	4091	4158	12944	2995	1634	1736	1387	5708	2153	1821	339	181	712	437	1158	186	56	295	164	777
D	U	27929	3093	8726	13481	2507	894	870	2619	6205	1430	540	357	931	2582	900	563	48	125	299	172	299	34	48	95	49	180
D	S	60689	6962	13181	33947	5736	2362	2349	5404	18313	4113	1991	1076	1969	8839	3139	2335	150	252	1075	621	1283	89	78	331	163	743
D	H	13338	1557	2550	6601	1706	738	536	1289	4359	1295	687	271	552	2231	964	855	54	50	266	214	470	16	21	76	65	266
D	P	4698	431	717	1909	444	678	205	410	1312	359	447	94	151	752	307	405	14	22	107	75	269	7	9	28	18	149
HS	N.A.	39179	5150	3694	10817	1877	1179	7806	7957	30297	7735	6127	3163	2396	12418	5520	6422	947	332	2157	1776	5706	419	82	553	469	3579
HS	U	27194	1435	2911	6044	942	428	1416	6005	14703	3203	1810	485	1655	5403	1993	1503	80	188	640	371	874	34	60	156	88	396
HS	S	115063	5887	9221	27058	4517	2156	7462	21329	80903	19064	12363	2813	6637	33957	14124	12922	602	783	4937	3564	9234	255	133	991	694	4389
HS	H	46034	2184	3173	9826	2074	1249	3087	9061	35667	10376	7807	1365	2974	15882	8184	8204	329	355	2485	2462	6054	158	58	456	526	3297
HS	P	15318	668	906	3022	590	689	1094	2576	10762	3073	3989	467	918	5112	2441	3513	130	126	831	807	2554	43	30	174	152	1239
SC	N.A.	23797	1644	1125	3461	656	475	2053	2037	8630	2309	2071	3112	2164	12308	6212	7838	1210	339	2856	3002	10464	721	101	788	956	9574
SC	U	12517	319	835	1647	269	116	300	1329	3521	823	490	281	1275	3969	1428	1314	71	158	525	312	953	14	35	134	83	526
SC	S	104900	2306	4294	12792	2286	1247	2595	9022	35117	8426	6247	3110	8634	46013	19781	19019	736	1034	7813	6386	17124	355	163	1634	1498	10288
SC	H	74983	1427	2497	7875	1704	1124	2031	6579	26848	7674	6060	2422	6258	34210	18595	18310	613	753	5835	6599	16571	334	117	1165	1491	11169
SC	P	39121	682	1074	3599	784	697	999	2945	12090	3438	3587	1359	2959	16315	8664	11779	410	380	3367	3265	11044	190	75	723	797	6920
BA	N.A.	6861	234	156	454	109	99	346	296	1366	436	482	548	345	2192	1307	2148	921	260	2591	3136	10832	632	70	877	1233	14004
BA	U	1742	25	83	138	34	9	24	139	298	72	50	22	155	383	194	177	26	129	314	210	483	6	28	66	55	351
BA	S	23562	213	394	1058	235	151	304	910	4131	1127	939	401	1142	6742	3114	3680	390	595	5235	4227	11587	214	110	1150	1046	9292
BA	H	21793	140	217	734	193	159	273	783	3277	1073	959	354	964	5649	3535	3797	362	477	3669	4941	11051	164	79	766	1212	9519
BA	P	55370	419	596	2129	509	392	770	2236	9753	2862	3083	1082	2620	15888	8752	11421	1042	1053	9540	10690	39633	606	183	2245	2810	31677
G	N.A.	3326	123	95	238	51	32	177	129	454	117	151	192	110	572	337	489	231	51	435	538	1969	512	63	478	562	6514
G	U	548	14	44	74	17	2	9	43	75	20	14	7	40	83	35	25	7	13	43	21	59	8	27	62	25	132
G	S	6294	86	144	398	77	29	119	225	869	222	150	104	198	1096	514	588	91	74	718	576	1757	119	64	737	445	3713
G	H	6029	80	88	275	64	41	89	228	840	220	203	90	187	1031	623	619	74	51	525	680	1769	115	47	373	624	3695
G	P	53423	296	355	1145	299	242	534	1155	4933	1535	1545	978	1449	8715	5246	6397	944	624	5644	6782	22731	1184	265	3012	3825	54361

matching table in 2007 : total households = 3,959,823

women's education	women's job	N.A.	D					HS					SC					BA					G				
		N.A.	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P
N.A.	N.A.		44621	32162	51521	9217	4275	48471	55348	121215	28676	16943	27314	27525	92072	38879	32788	8421	5739	27795	21766	51743	3502	1093	6061	5760	45268
D	N.A.	45493	9363	11068	21249	3519	1820	3707	3775	10519	2270	1281	1556	1345	4642	1666	1339	317	220	759	404	940	141	49	199	134	665
D	U	22766	2157	8298	10800	1995	662	843	2680	5039	1134	509	331	940	2252	712	443	53	151	353	154	264	19	27	98	44	120
D	S	43508	4360	8839	21735	3410	1488	1958	4433	12976	2849	1350	926	1561	6328	2075	1576	171	233	957	451	970	65	47	219	117	553
D	H	9977	963	1964	4214	1262	538	489	1080	3316	966	602	247	415	1663	791	618	30	54	218	179	369	18	6	63	39	225
D	P	3331	254	410	1136	285	543	169	293	911	272	334	114	151	538	267	342	25	13	110	74	191	11	3	27	19	175
HS	N.A.	46793	4649	3388	8745	1463	1000	8999	8837	27989	7130	5770	3961	2748	12693	5659	6358	1246	457	2599	2114	6345	559	92	581	496	3823
HS	U	29906	1395	2940	5041	866	353	1995	7347	14891	3308	1750	675	2111	5423	1969	1536	137	311	782	446	947	35	73	160	92	427
HS	S	116195	5013	7173	19394	3227	1614	8483	21951	73318	17702	11792	3725	7254	32271	13238	11887	831	951	5729	3995	9359	304	171	1009	775	4497
HS	H	46808	1792	2615	7536	1577	995	3888	10015	34145	10577	8128	1852	3408	15704	8236	8028	487	487	2803	2780	6476	176	79	505	527	3394
HS	P	16335	613	793	2347	447	559	1332	2904	10710	3178	4308	701	1108	5110	2621	3814	208	155	1129	983	2855	69	31	176	188	1407
SC	N.A.	32800	1665	1147	3200	615	458	2875	2687	10150	2794	2597	4330	2912	14282	7123	8827	1584	481	3610	3730	12689	929	100	909	1150	10922
SC	U	15073	397	862	1477	258	142	468	1865	4177	909	576	459	1594	4478	1662	1389	87	243	723	441	1083	37	49	151	96	624
SC	S	119029	2479	3932	10611	1981	1031	3880	11350	38293	9344	6781	4497	10077	47960	20557	19280	1099	1322	9022	7184	18364	482	235	1662	1452	10946
SC	H	80808	1295	2216	6457	1422	991	2882	8165	28600	8709	6820	3369	7485	36181	20460	19023	993	1006	6795	7551	17554	418	183	1162	1611	11655
SC	P	42785	676	1024	2995	688	662	1454	3687	13422	3949	4461	1977	3587	17787	9310	13033	600	503	3903	3714	12274	288	70	765	846	7583
BA	N.A.	9943	230	208	500	120	117	571	505	2025	610	775	940	508	3076	1810	2976	1656	415	4117	4788	17309	1187	111	1237	1755	20068
BA	U	2663	41	117	199	39	20	65	291	463	112	89	58	253	595	227	250	48	255	495	302	719	18	40	85	69	524
BA	S	31106	247	413	1155	255	187	530	1517	5782	1613	1455	711	1776	8891	4245	4712	654	963	7538	5779	15493	334	131	1557	1329	11987
BA	H	27934	155	260	752	233	157	439	1269	4813	1718	1583	661	1409	7497	4939	4961	641	732	5306	7130	15215	289	103	987	1656	12280
BA	P	68325	414	629	1769	456	456	1222	3213	12366	4013	4430	1887	3690	19455	11430	14713	1982	1594	12908	14525	52577	991	245	2721	3636	39899
G	N.A.	4204	99	66	178	49	30	225	150	547	165	168	428	150	729	487	628	572	81	866	979	3901	995	70	656	939	10972
G	U	546	5	37	60	11	8	11	52	85	12	12	12	42	120	31	43	6	22	66	34	106	16	47	62	52	174
G	S	7439	65	91	256	55	41	125	295	958	253	214	179	265	1336	691	756	162	132	1065	852	2575	198	114	852	624	5218
G	H	7070	51	69	182	45	26	104	229	856	311	286	186	258	1240	829	863	148	130	819	1118	2636	191	66	526	895	5367
G	P	72079	289	387	1042	271	260	990	2000	7452	2454	2474	1876	2574	13479	8042	9571	2006	1166	9631	11264	36629	2348	437	4253	5677	79360

men's job (columns, second header row); men's education (column groups); women's job and women's education (rows)

matching table in 2012 : total households = 4,108,824

women's education	women's job	N.A.	D					HS					SC					BA					G				
		N.A.	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P
N.A.	N.A.		68696	36349	53342	9971	4464	82697	67287	131218	30966	17390	47000	35836	103825	42429	34635	11599	6655	29242	22005	53331	4547	1225	6380	5749	46293
D	N.A.	56103	9346	12764	21804	3808	2072	4176	4448	10497	2307	1190	1922	1595	5042	1710	1308	343	262	847	391	1031	138	57	195	108	728
D	U	23704	2180	8340	9698	1948	583	895	2592	4326	998	416	381	932	1911	668	391	74	174	330	156	284	37	42	64	35	156
D	S	42518	4171	8397	18702	3297	1213	2135	3913	10125	2304	1126	980	1590	5420	1777	1233	194	222	891	434	944	64	43	218	97	511
D	H	9254	844	1979	3536	1079	411	528	977	2571	770	378	241	395	1261	586	456	39	38	197	120	289	19	6	54	52	195
D	P	3354	287	439	928	251	453	157	291	761	219	268	90	142	486	209	257	20	15	81	60	192	13	6	23	15	114
HS	N.A.	64588	5110	3918	8771	1492	843	9985	10168	28346	7180	5484	4619	3370	12966	5614	5805	1229	500	2562	1897	5960	515	89	528	476	3549
HS	U	31962	1381	2778	4225	720	290	2314	7363	12986	2984	1548	903	2089	5100	1795	1394	152	316	807	387	893	60	71	152	85	447
HS	S	115294	4779	6478	15221	2650	1282	9644	21167	61256	14612	9433	4225	7201	28205	11171	9794	869	977	4940	3319	8078	311	164	828	668	3911
HS	H	41258	1685	2304	5350	1166	693	3973	8846	26790	8038	6177	1993	3195	12663	6342	6016	460	421	2237	2185	4895	179	53	347	422	2492
HS	P	15618	572	678	1863	378	419	1463	2906	8811	2592	3327	822	1071	4407	2129	3036	245	143	899	717	2437	79	23	171	165	1129
SC	N.A.	49459	2217	1634	3898	712	465	4039	3992	12206	3146	2693	5770	3893	16786	7866	9149	1805	588	3693	3660	11920	908	112	940	1025	10202
SC	U	18633	435	972	1545	278	102	735	2085	4326	1015	557	685	1934	4714	1674	1390	129	275	684	451	1084	47	54	130	102	628
SC	S	135165	2812	4323	10349	2009	961	5160	13061	38462	9331	6476	5865	11688	47847	19409	17860	1317	1499	8528	6654	16575	504	214	1520	1300	9546
SC	H	78482	1476	2277	5684	1172	770	3399	8386	26338	7526	5955	4027	7725	32562	17679	15923	960	992	5957	6137	14622	415	145	1029	1220	9374
SC	P	43778	760	1104	2860	618	541	1873	4122	12816	3775	3982	2375	4028	17096	8566	11459	730	551	3534	3301	10703	319	86	619	758	6234
BA	N.A.	13036	286	298	677	166	109	762	728	2413	751	838	1284	704	3772	2135	3108	1845	559	4210	4638	17648	1148	102	1434	1801	20346
BA	U	3161	37	146	232	40	21	84	340	596	147	95	81	318	620	267	255	65	232	489	295	739	18	42	89	58	535
BA	S	36578	307	552	1313	288	189	789	1973	6492	1716	1410	1088	2168	10042	4661	5020	869	1090	7521	5725	15479	399	145	1450	1410	11264
BA	H	28590	185	287	784	200	146	554	1513	5056	1697	1527	876	1736	7843	4985	5030	753	732	5141	6549	14556	333	98	954	1593	11510
BA	P	69703	513	808	1943	438	425	1582	3910	12682	3957	4165	2551	4287	19966	11189	14136	2347	1751	12777	14021	49106	1116	309	2580	3420	36827
G	N.A.	5145	75	83	191	42	33	276	172	607	192	239	450	182	888	515	772	568	103	896	1128	4634	994	89	819	983	12417
G	U	672	6	31	39	9	4	15	41	79	20	13	15	59	89	39	54	9	14	64	48	129	18	30	61	20	219
G	S	8844	69	118	265	64	33	156	296	1054	271	234	259	337	1554	820	792	221	176	1186	1005	2825	191	101	881	602	5182
G	H	7446	34	70	147	42	27	130	232	755	286	280	196	279	1258	852	790	197	119	845	1202	2773	232	54	462	830	5285
G	P	75949	348	465	1134	296	286	1281	2653	8801	2673	2706	2490	3413	15728	9082	10261	2660	1436	10543	12034	39097	2403	477	4318	5920	81463

men's job (columns, second header row); men's education (column groups); women's job and women's education (rows)

matching table in 2017 : total households = 4,067,031

women's education	women's job	N.A.	D					HS					SC					BA					G				
		N.A.	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P	N.A.	U	S	H	P
N.A.	N.A.		67201	33309	48263	9639	5148	93060	68356	127570	31544	19036	49732	37200	102675	42823	36088	13026	7605	31178	23420	58616	4886	1532	7425	6424	49581
D	N.A.	50738	7622	11339	19186	3269	2233	3681	4152	9178	2165	1286	1731	1490	4607	1604	1360	351	255	858	495	1229	167	51	230	142	929
D	U	20860	1817	6726	7948	1629	591	779	2196	3668	831	424	390	838	1702	587	379	71	145	340	161	316	23	35	88	42	172
D	S	36538	3401	6769	15218	2782	1291	1760	3168	8162	1847	1120	891	1266	4502	1627	1238	194	198	818	492	1088	63	38	181	133	666
D	H	8683	731	1660	2919	1008	483	448	838	2133	640	373	219	359	1134	543	439	49	50	191	180	367	17	18	52	48	238
D	P	3621	258	431	963	269	459	163	300	756	214	235	94	119	476	219	294	23	12	94	83	241	8	6	21	33	152
HS	N.A.	66453	4471	3754	7853	1385	1002	10100	9966	26792	6638	5436	4399	3144	11737	4916	5503	1170	505	2402	1833	5451	458	83	535	461	3517
HS	U	31506	1207	2347	3821	627	300	2297	6792	11771	2672	1647	913	1920	4467	1589	1259	160	310	793	434	968	76	54	166	103	476
HS	S	104998	3986	5413	12601	2352	1307	9066	18370	52262	12188	8839	3887	6024	23240	9439	8764	928	867	4456	3141	7547	322	156	893	659	3748
HS	H	36821	1443	1926	4552	933	686	3739	7441	21665	6558	5331	1751	2542	9687	4964	5100	437	395	1801	1771	4206	152	64	367	406	2112
HS	P	15552	561	748	1717	363	426	1474	2820	8183	2418	3160	732	1066	4026	1970	2897	222	161	865	766	2403	88	38	164	165	1214
SC	N.A.	50398	2232	1680	4055	720	530	4388	4000	12509	3232	2958	5843	4009	16683	7562	9449	1701	608	3516	3485	11592	873	130	962	1050	9264
SC	U	19219	457	949	1592	235	139	730	2193	4125	963	649	723	2035	4757	1717	1520	143	307	747	503	1167	51	50	147	107	641
SC	S	126327	2711	4005	9181	1827	1070	5157	12044	34876	8489	6640	5890	10898	43908	17750	17267	1328	1315	8026	6128	15842	511	231	1570	1375	8781
SC	H	71047	1388	2131	5197	1080	843	3364	7770	23637	6693	6023	3953	7056	29287	15759	14857	1001	876	5364	5560	13539	384	152	994	1215	8194
SC	P	42404	817	1175	2785	621	621	1985	4192	12582	3493	4158	2519	4059	16582	8215	11633	737	572	3434	3340	10469	317	101	635	712	6147
BA	N.A.	14142	318	354	753	134	133	898	860	2787	839	998	1358	854	4178	2240	3363	1857	578	4285	4688	18896	1025	132	1434	1875	20192
BA	U	3729	57	190	231	57	19	94	396	671	154	110	105	336	770	328	325	84	281	570	356	910	22	39	108	89	617
BA	S	39422	391	609	1400	338	226	935	2254	6937	1858	1706	1191	2311	10400	4810	5329	935	1161	7664	6022	17154	373	184	1538	1466	12307
BA	H	29978	224	357	865	224	204	659	1627	5380	1975	1790	984	1839	8223	5113	5343	800	815	5204	6941	16361	316	120	1068	1744	12118
BA	P	74617	601	918	2323	539	601	1866	4186	13610	4310	4824	2848	4572	21203	11921	15476	2623	1945	13596	15281	55408	1125	367	2973	3913	39321
G	N.A.	5464	132	92	232	44	46	336	244	757	201	284	531	213	1070	630	848	660	131	1013	1222	5305	935	104	841	1172	13330
G	U	915	10	30	44	13	5	14	82	128	27	17	27	55	141	50	65	15	46	79	62	175	21	44	79	50	272
G	S	10744	92	128	323	74	57	217	364	1271	388	331	302	418	1909	912	1053	249	199	1431	1209	3659	240	138	977	773	6260
G	H	9124	70	82	196	50	56	166	335	1020	386	306	263	324	1582	1019	1035	238	156	1044	1519	3581	235	106	615	1074	6683
G	P	82308	426	628	1484	355	365	1532	3079	9921	3087	3360	2749	3725	17172	9936	11912	2811	1731	11973	14054	47319	2563	556	5461	7291	91458

men's job (columns, second header row); men's education (column groups); women's job and women's education (rows)