Assortative Marriages and Household Income Inequality

Miguel Olivo-Villabrille*

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Abstract

Income differences across households are larger the more similar are the earnings potentials of breadwinners within the household. As such, the tendency for individuals to marry people similar to them has likely served to amplify inequality across households. In this paper I study the effect that educational assortative matching has on income inequality in the United States. Quantifying this effect presents a serious empirical challenge because education and marriage patterns are jointly determined equilibrium outcomes. Observed patterns of marriage are an outcome of a two-sided dynamic matching process. Individuals on both sides of the market take as given the distribution of available singles at each point in time. Anticipating this process, forward looking individuals make pre-marital investments in human capital to improve future prospects on the marriage and labor markets. As such, I develop a dynamic discrete choice model of endogenous educational attainment and subsequent marriage market matching. I estimate the parameters of the model using US Census data combined with information on marriage registrations. I use the estimated model to perform a series of counterfactual experiments that help quantify the role of female educational attainment and assortative matching on education in amplifying income inequality across households.

Keywords: assortative matching, marriage, household income, inequality, education.

JEL classification: J12, D10, I24, D39.

*ARC Centre of Excellence in Population Ageing Research, University of New South Wales, Sydney, NSW, Australia. Email: m.olivo@gmail.com. I thank Arvind Magesan, Eugene Choo, Pamela Campa, and Atsuko Tanaka for their guidance. I have benefited from discussions with Michael Keane, Luigi Pistaferri, Aloysius Siow, Trevor Tombe, Alex Whalley, Basit Zafar, and Arezou Zaresani. I also thank seminar participants at the University of Calgary, Canadian Economics Association Annual Meeting 2015, the Empirical Microeconomics Workshop 2016 in Banff, ASSLE 2017, and the Demographics, Immigration, and the Labor Market Conference 2018.

1 Introduction

People marry partners who are similar to themselves. In particular, people tend to marry partners with similar education level. This is known as "positive educational assortative matching." While it is not a new phenomenon, the degree to which people marry partners of similar education level has potentially serious economic implications. For example, the patterns of marriage can determine child success in school, social development and other cognitive and behavioral characteristics (Beck and González-Sancho, 2009). It also affects the stability of marriages (Bruze et al., 2015) and intergenerational mobility (Schwartz, 2013).

In this paper I focus on the effect of educational assortative matching on household income inequality. The proportion of marriages with positive educational assortative matching has been increasing since the 1940s (Schwartz and Mare, 2005). Over the same time period, income inequality rose by 22.8% (Atkinson and Morelli, 2014). There are reasons to believe that the two trends are related: since education at least partly explains earnings, the more similar the education of spouses, the more unequal income across households will be.[1] However, quantifying the effect presents difficulties.

First, the level of assortative matching in equilibrium is a function of the distribution of characteristics and preferences of available singles on the marriage market. If all available singles have the same level of education then there would be perfect assortative matching on education, even if people would prefer to marry a partner of a different education level. The equilibrium level of educational assortative matching also depends on preferences for partner's education. If available singles do not consider the education of their potential partner when making marriage decisions, then the level of educational assortative matching would be low. This would occur even when there are educated singles available to marry.

[1] See also Fernandez and Rogerson (2001).

Second, the distribution of education across singles is endogenous as it responds to expectations about the marriage and labor markets. In the labor market, a higher education level commands higher wages and better employment prospects. More educated individuals also obtain better outcomes in the marriage market (Chiappori et al., 2009). As forward-looking individuals internalize the future market returns to educational investments, the interaction between education, and outcomes in the labor and marriage markets must be addressed jointly when quantifying the effect of educational assortative matching on household income inequality.

In this paper, I develop and estimate a structural model of educational attainment and marital decisions. The model has two stages nested within a dynamic discrete choice equilibrium framework. In the first stage, individuals make educational choices; and in the second stage, they decide whether to marry and who to marry – which partner type to marry.[2] This framework allows me to estimate preferences for partner types – which govern the formation of marriages, given a distribution of available singles. I can also estimate the effect of marriage and labor market prospects on educational decisions – which in turn determine the distribution of available singles. More importantly, the framework allows me to examine the effect of preferences for partner's education and the distribution of available singles on the distribution of marriages, the level of assortative matching, and resulting household income inequality. While the present model does not allow for endogenous determination of wages at the individual level,[3] I take into account the distribution of wages conditional on observed characteristics when performing counterfactual experiments.

Using the framework of Choo (2015), I find that age similarity is a strong factor in determining the pattern of marriages. Specifically, people prefer matches in which the husband is slightly older than the wife. Education also plays an important role in the formation of

[2]Partner types are defined by age, level of education, and race.
[3]This is due to the model not allowing for within-marriage decision-making.

marriages. People prefer to match with partners of the same level of education. Finally, Race of the partners also affects the pattern of marriages. People largely prefer to marry partners of their same race.

Despite the relevance of the estimates, my primary objective is to use the model to examine the effect of assortative matching on inequality. To that goal, I decompose the distribution of income for married couples into the distribution of marriage types – defined by partner types – and the distribution of household income conditional on marriage type. Preferences and the distribution of available singles determine the distribution of marriages. In turn, the distribution of marriages affects the (unconditional) distribution of household income through the conditional distribution of household income given marriage type.

Recognizing that the level of assortative matching in the marriage market is an outcome that depends on preferences for partners education and on the distribution of available singles, I perform two counterfactual experiments that vary the level of educational assortative matching endogenously through both channels – preferences and the distribution of singles. First, holding (estimated) preferences constant, I change the distribution of available singles in the marriage market, particularly by increasing the level of education in the population of singles. Second, holding the distribution of available singles in the marriage market constant, I change preferences for partner's education – which also changes the marriage market returns to education.

My results indicate that assortative matching alone has little effect on household income inequality. Rather, assortative matching acts as an amplifier of the underlying inequality in wages across educational groups. In particular, the availability of more educated singles in the marriage market does not change the patterns of marriages that form, and as a consequence the level of inequality does not change. Only when also imposing a more unequal distribution of incomes, inequality increases. Further, I explore the resulting inequality if people do not hold preferences for partner's education levels. I find that while the resulting pattern of marriages changes (reflecting less assortative matching along education), inequality remains almost the same.

My paper relates the literature on educational matching. Chiappori et al. (2009) builds an theoretical equilibrium model of premarital schooling and marriage patterns to explain the increase in women's education. Chiappori et al. (2017) use a static equilibrium model of educational matching to estimate the returns to schooling within marriage. Chiappori et al. (2015) develop a three-stage model of premarital investment, static marriage, and labor supply. Finally, Bruze et al. (2015) estimate a partial equilibrium dynamic model of marriage and divorce. While I also estimate a matching model, my work departs from the previous literature in two ways. First, I employ the dynamic equilibrium model in Choo (2015). Dynamics are important in the marriage market as individuals are forward-looking and make marital decisions based on their expectations about the future.[4] Second, in contrast to studying marriage patterns, my main objective is to examine the effects of assortative matching on household income inequality. It is important for my purposes to estimate a dynamic matching model on age, education, and race, as labor income has large gradients along those characteristics.

In addition, my paper also relates to life-cycle models of educational attainment and marriage. These models are often elaborate and also include individual decisions on fertility, and labor supply. Keane and Wolpin (2010) study the differences in the behavior of black, Hispanic, and white women regarding the interaction of education, labor supply, marriage, fertility, and welfare participation. They estimate a model that endogenizes all those decisions in a life-cycle framework. However, they consider marriage as a one-sided decision made by women. Eckstein and Lifshitz (2011) develop a model of female labor supply and

[4]Failing to account for dynamics in marital decisions leads to underestimation of the gains from marriage (Choo, 2015).

compare its performance to a static model and a reduced form model. Their model treats schooling, fertility and marriage as exogenous factors. Finally, Eckstein et al. (2019) estimate a model that includes endogenous education, labor supply, marriage and fertility. They explore the factors behind the rise in the employment rates and wages of married women. One major difficulty of these life-cycle models is that they are not able to incorporate marriages of heterogeneous ages. This is because solving a finite horizon model that allows for marriages between individuals of different ages is "essentially impossible" (Eckstein et al., 2019). This paper bypasses that difficulty.

My work also relates to a body of work documenting the relationship between educational assortative matching and household income inequality. This literature has not reached a clear conclusion on the magnitude or direction of the effect. Kremer (1997); Cancian and Reed (1999); Breen and Salazar (2011); Hryshko et al. (2014) find little to negative effect of assortative matching on inequality. However, Fernandez (2005); Schwartz (2010); Greenwood et al. (2014) find that inequality increases with the level of assortative matching. These opposite findings could be due to confounding effects coming from changes in the distribution of available singles when measuring assortative matching.[5] A paper that controls for the distribution of singles is Greenwood et al. (2016) where they develop a marriage search model that accounts for marriage, divorce, educational attainment, and labor force participation of married women. They find that the increased returns to education in the labor market, higher educational attainment and increasing educational assortative matching magnifies income inequality across households. However, they depart from the canonical model of matching with transfers of the marriage market introduced by Becker (1973, 1974).[6] Eika et

[5]See Liu and Lu (2006).

[6]Becker proposed that people find partners to marry in marriage market as in a matching game. Greenwood et al. (2016) uses a random search framework: Individuals meet potential partners by drawing from the distribution of singles and deciding whether to marry or not. This is important, because while the distribution of singles can respond to educational choices, individuals can always meet a new partner by obtaining a new draw from the distribution of singles. There is no scarcity of singles. All this implies that there are no returns to education in the marriage market and matching on education is ad-hoc. In addition, their model neglects both heterogeneity on age and the effect of age on the marriage market value of individuals. The

al. (2018) also analyze the effect of educational assortative matching on household income inequality in the United States and Norway. They decompose the distribution of household income into the contributions of assortative marriages, and returns to education in the labor market. They find that educational assortative matching has a sizeable effect on cross-sectional inequality in household income, but it has a negligible effect on the trends in inequality over time. My paper contributes to this literature by taking into account the endogenous acquisition of education, the resulting distribution of singles, and preferences for partner types in an dynamic matching equilibrium framework.[7] As such, my work forms a connection between the literature on educational matching and the literature examining educational assortative matching and inequality.

2 Background and Data

I provide historical context in section 2.1, and explore the possible causes of the increase in educational assortative matching in section 2.2. I then describe the data in section 2.3.

2.1 Income Inequality in the United States

Income inequality in the United States has been increasing since the mid 1970s. This increase follows a long period of stability attributed to the Great Depression and both World Wars. Figure 1 shows the evolution of the Gini coefficient of equivalent household disposable income in the US from 1944.[8] Since the 1970s, wage dispersion increased for both men and women. Figure 2 shows that the dispersion in earnings at the top of the income distribution has also widened. In addition, the returns to education increased sharply for both genders

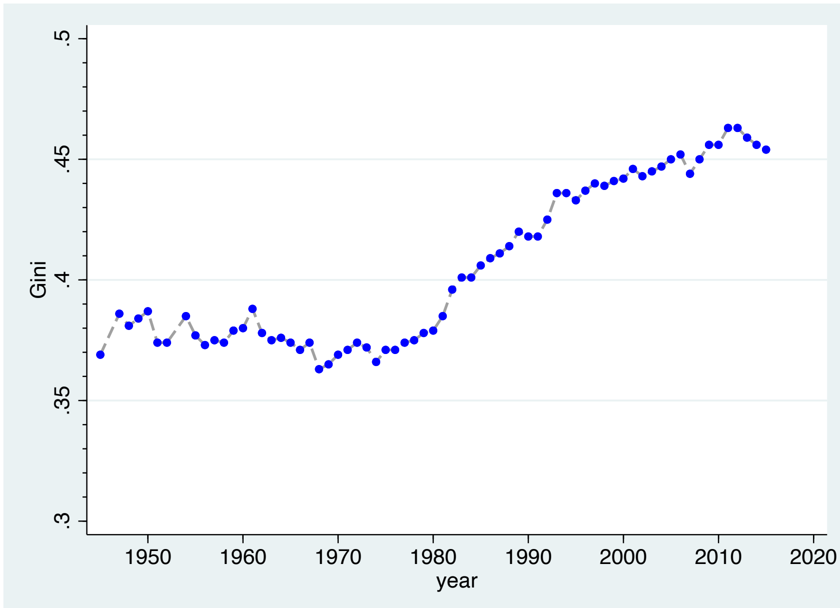
latter is a serious drawback since women's biological fertility decreases with age and it could be an important cause of why we observe an increase in assortative matching along education (Low, 2016; Chiappori, 2017).

[7]These features are important for understanding assortative matching, as educational choices made earlier in life influence marital decisions later on (Blossfeld, 2009).

[8]Household disposable income includes income from all sources and transfer payments, net of direct taxes and social security contributions. The equivalence scale is the modified OECD scale, which gives weight of 1 to the first adult, 0.5 to each additional adult, and 0.3 to each child. Total household disposable income is divided by the sum of weights in the household.

the 1980s. The increase in earnings inequality along with the increased correlation between earnings of spouses have been the main drivers of the rise in income inequality across families (Katz and Autor, 1999).

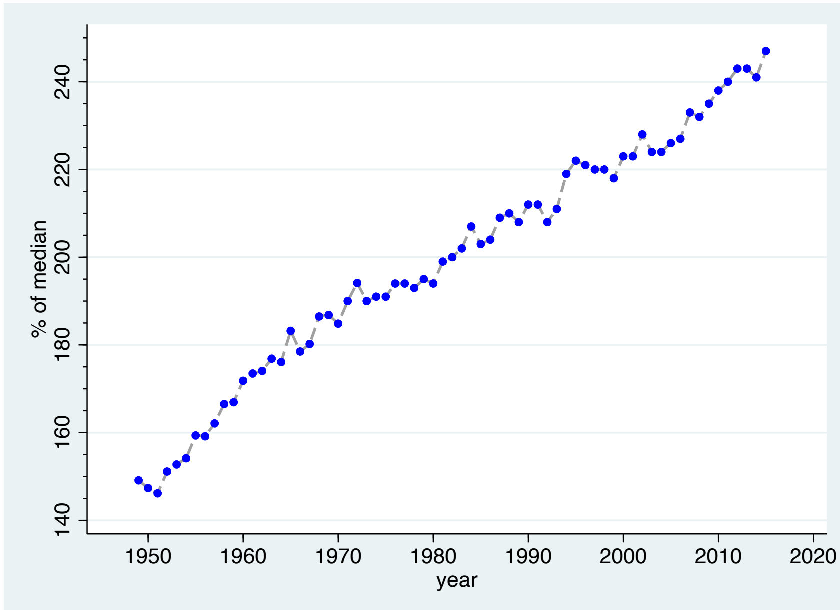
Figure 1: Gini coefficient of household income over time.



Source: Atkinson and Morelli, 2014.

The rise in income inequality across individuals has been mainly attributed to four factors (see Katz and Autor, 1999; Autor et al., 2008): First, skill-biased technological change increased the returns to education. Second, the reduction in the cohort size of workers entering the labor market, and an increase in unskilled immigration slowed down the relative supply of skills. Third, an increase in trade with developing countries and foreign outsourcing of jobs reduced domestic manufacturing production. Finally, changes in labor market institutions such as the decline of labor unions, erosion of the real minimum wage and wage setting norms likely also contributed to the increase in individual-level inequality.

Figure 2: Household earnings at top decile as % of median.



Source: Atkinson and Morelli, 2014.

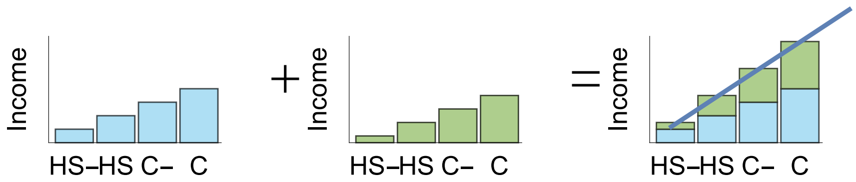
2.2 The Role of Educational Assortative Marriages

In addition to the role played by the returns to skill, globalization and labor market institutions, family formation patterns have also likely contributed to cross-household inequality (Burtless, 1999). If acquiring more education is rewarded in the labor market, and marriages form on the basis of similarity of spouses' education, then the distribution of cross-household income would reflect patterns of marriage formation. Figure 3 illustrates this effect. The graphs on the left represent income levels of spouses for various education levels, and the graph on the right represents total household income under perfect positive educational assortative matching.[9] The slope of the line connecting the top of each bar is a measure of inequality.[10]

[9]The effect of educational assortative matching on inequality would be less pronounced if there was less than perfect assortative matching but would still be positive.

[10]The steepness of the imaginary line measures how much income changes when household type increases by one educational category.

Figure 3: Effect of assortative matching on inequality.



The proportion of marriages with partners of similar education has been increasing since the 1940s (Schwartz and Mare, 2005). Figure 4 illustrates the increase in assortative matching since 1968 using CPS data. The figure shows the γ_t coefficients of regressing[11] years of education of the wife on years of education of the husband, controlling for time dummies and baseline correlation between spouses' education:

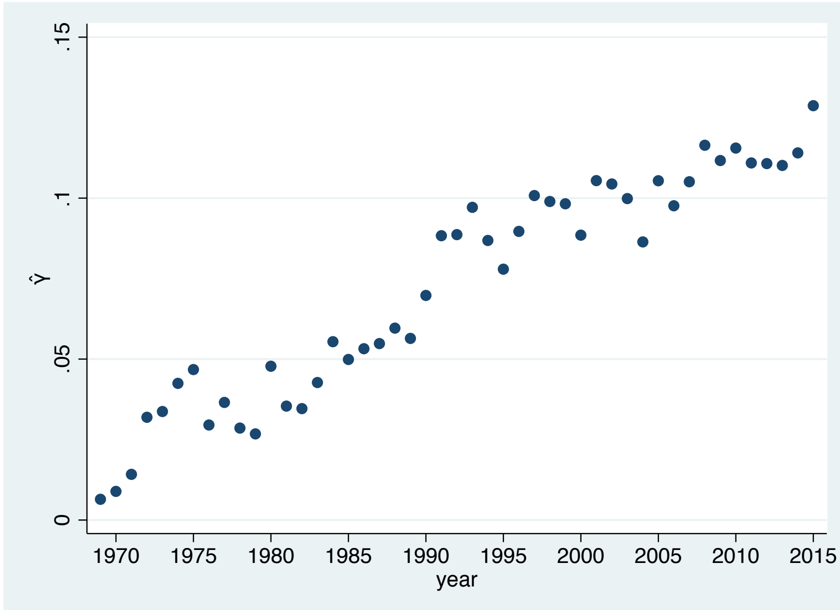
$$edu^w_{mt} = \beta edu^h_{mt} + \gamma_t \times edu^h_{mt} + \delta_t + \varepsilon_{mt}.$$

where edu^w denotes years of education of the wife, edu^h is years of education of the husband, t indexes years and m indexes marriages. γ_t measures the increase in assortative matching in year t compared to the baseline year 1968 ($\widehat{\beta} = 0.3560$). The graph shows an increase in assortative matching over time.

The observed increase in assortative matching over time could be due to 3 factors. First, there could be an increase over time in preferences for partners of similar education levels. Second, holding preferences unchanged, there could be an increase in the supply of more educated individuals entering the marriage market (this means that the observed lower level of assortative matches in the 1960s and 1970s was due to supply restrictions). Finally, we could also observe an increase in assortative marriages due to an increase in the propensity to marry of more educated individuals relative to less educated individuals. I can separately

[11] This regression is similar to the one in Greenwood et al. (2016), but they only consider college education in Census years.

Figure 4: Assortative matching over time.



assess these factors in the model presented in this paper.[12]

2.3 Data

The data sources used in the estimation are the US Census, and the Marriage and Divorce tables of the National Vital Statistics System. The US Census is available every 10 years and contains information on age, education, race, marital status, school attendance, and other demographic variables. The US Census is available for every state.

I use the Marriage and Divorce tables of the National Vital Statistics System from the NBER collection. These tables contain weighted samples of the marriages certificates for 42 reporting states and includes information on age and years of education of the partners.

[12]Some authors have argued that recently marriages form on the basis of consumption complementarities rather than production complementarities (Stevenson and Wolfers, 2007). Essentially, the argument relies on the advancement of household technology that increases the opportunity cost for women of specializing in household work. This results in women acquiring more education than in the past and both sexes preferring partners with similar tastes with whom to enjoy their free time together. Then, if marriages form on the basis of the consumption model, the pattern of marriages should reflect similar preferences for consumption and leisure, which likely implies positive assortative matching along age, educational background, occupation, etc. (Isen and Stevenson, 2010).

However, information of age, years of education and race is available only for 26 states in 1980.[13] For consistency, I only use those same states from the Census data.

I consider individuals aged between 16 and 65 and with education between 10 years of education – corresponding to grade 10 of high school – and 16 years of education – corresponding to finishing a college degree in four years – that are not attending school.[14] I consider ages starting at 16 because it is the minimum age in which individuals can get married in the United States, and it is also the minimum age at which individuals can legally drop out of high school in many states. The maximum age of 65 is the retirement age.

Regarding the range of education, grade 10 corresponds to age 16, and it is also the age in which compulsory education ends. I only consider up to college education, because I require that education be acquired contiguously during early lifetime for the first stage of the model below. This assumption of contiguous education is unlikely to hold beyond a college degree since many individuals do not attend graduate school immediately after finishing college.

I use the data from the US Census to obtain the number of available single men and women by age, years of education and race. Table 2 presents descriptive statistics for singles. The Marriage and Divorce Tables from the National Vital Statistics System contains data on marriages by age, years of education and race of the partners. I get the distribution of new marriages by type from there. Table 2 presents descriptive statistics from the sample of registered marriages; Table 3 shows the distribution of marriages by race.

I also use the Census data to obtain the distribution of income by age, education and race for single and married individuals. For married households, I use the combined labor

[13]The states with available information in 1980 are: Arizona, Arkansas, Hawaii, Illinois, Kansas, Louisiana, Maine, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Mexico, North Carolina, North Dakota, Oklahoma, Rhode Island, Tennessee, Texas, Utah, Vermont, Virginia, Washington, Wisconsin, and Wyoming.

[14]Individuals attending school are considered to be out of the marriage market (this is the second stage in the model below).

Table 1: Descriptive statistics for available singles.

Men					
Variable	Wgtd Obs	Mean	Std Dev	Min	Max
Age	4,876,800	29.94	11.57	16	65
Educ	4,876,800	12.65	1.71	10	16
White	4,006,500	82.15			
Black	718,500	14.73			
Other	151,800	3.11			
Women					
Variable	Wgtd Obs	Mean	Std Dev	Min	Max
Age	5,546,860	34.78	14.26	16	65
Educ	5,546,860	12.55	1.65	10	16
White	4,311,180	77.72			
Black	1,074,900	19.38			
Other	160,780	2.39			

Table 2: Descriptive statistics for married individuals.

Men					
Variable	Wgtd Obs	Mean	Std Dev	Min	Max
Age	383,870	26.96	8.30	16	65
Educ	383,870	12.73	1.63	10	16
Women					
Variable	Wgtd Obs	Mean	Std Dev	Min	Max
Age	383,870	24.56	7.39	16	65
Educ	383,870	12.57	1.56	10	16

Table 3: Distribution of marriages by race.

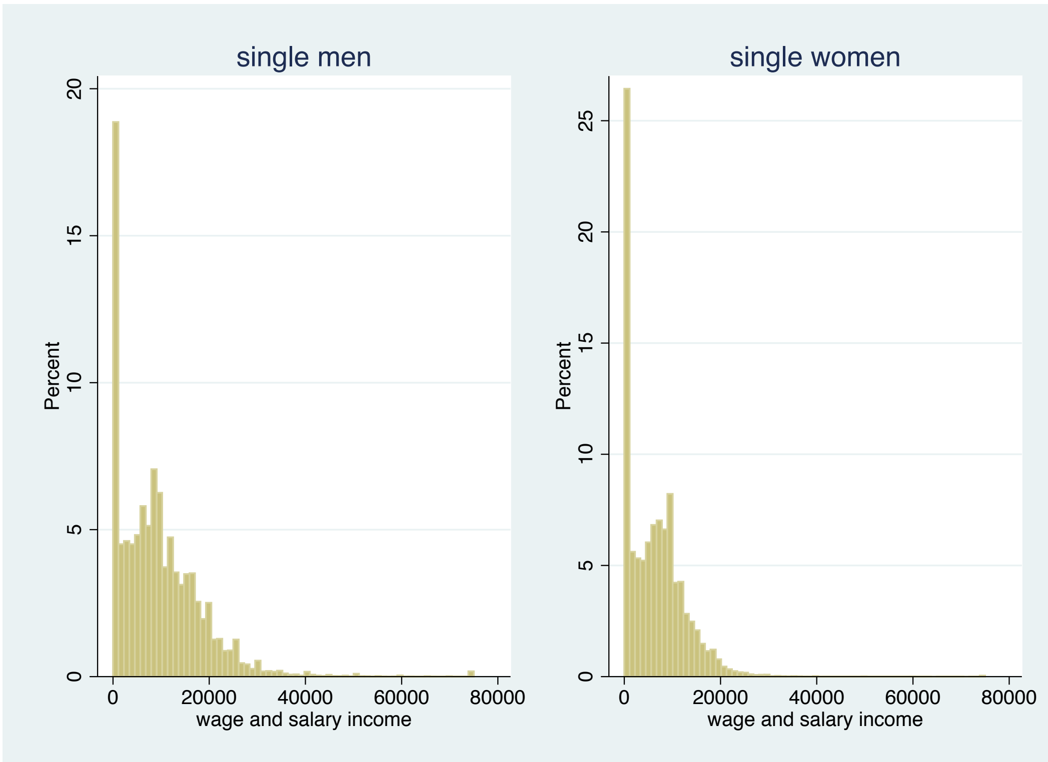
	Wife race			
Husband race	White	Black	Other	Total
White	87.67%	0.15%	0.56%	88.38%
Black	0.50%	9.41%	0.06%	9.98%
Other	0.48%	0.01%	1.16%	1.65%
Total	88.65%	9.58%	1.78%	100%

income[15] of the couple. I assume that single individuals form their own household, and their total household income is simply equal to their individual labor income. Figures 5, 6 display the distribution of labor income for single and married individuals respectively, while figure 7 shows the distribution of total household income for married couples. Married men are more

[15]Labor income includes pre-tax wage and salary income in the year. It comprises wages, salaries, commissions, cash bonuses, tips and other money income received from an employer.

likely to work than single men (as illustrated by the smaller share of men with 0 income), while the opposite is true for women. Also, married men earn more on average than single men, while again the opposite is true for women.

Figure 5: Distribution of labor income for singles.



To obtain the education history of individuals, I construct a panel by backtracing each individuals' educational decisions in their early life. Specifically, for a given pair of age and years of education, I calculate the educational decisions of the individual from age 16 until the observed age in the Census assuming that education is acquired contiguously during lifetime. For education between high school and college degree, this assumption of contiguous education is not very restrictive, but for post-graduate education it would be hard to sustain as many individuals accumulate some work experience before pursuing a graduate degree.

Figures 8 and 9 present the distributions of age and education for available singles in 1980. The fatter tails in the distribution of age for women reflect the fact that women live longer

Figure 6: Distribution of labor income for married individuals.

than men. Women are also more likely to have a high school degree than men.

Figure 10 presents a scatter plot of the patterns of marriage in 1980 by ages of the couple, where a larger marker size represents a higher frequency of marriages and the red diagonal is a 45° line. Table 4 presents the same information in a tabular format. The first number in each cell represents the raw frequency of the match, while the second number represents its relative frequency. Some stylized facts are easily noticeable: (Ia) there is a strong degree of assortative matching on age (that is, individuals marry partners with similar age); (IIa) most marriages occur early in life, between ages 18 to late 20s and early 30s; (IIIa) while older individuals are less likely to marry, older women marry less often than older men; and (IVa) men are slightly older than their wives. All of this implies that there must be negative gains from marriage for partners of dissimilar ages, and in particular for older women.

Figure 7: Distribution of total household income for married individuals.

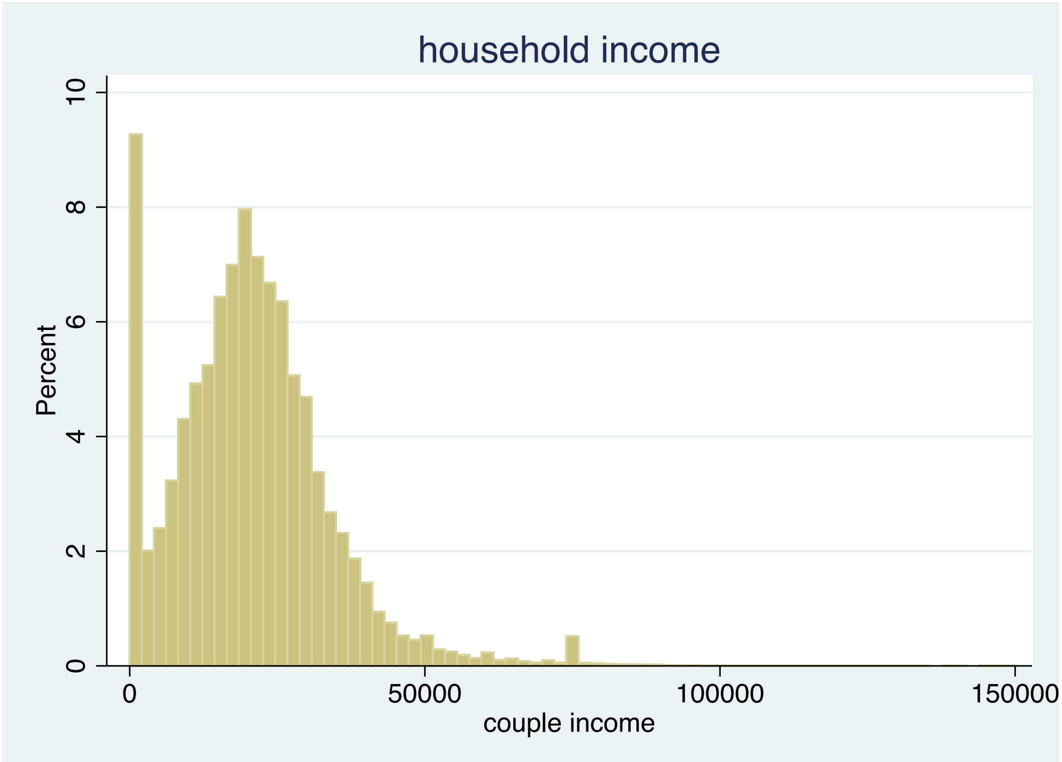


Figure 8: Available single individuals by age.

Figure 11 shows the corresponding scatter plot of the patterns of marriage in 1980 by years of education. As before, a larger marker size represents a higher frequency. Red lines

Figure 9: Available single individuals by years of education.

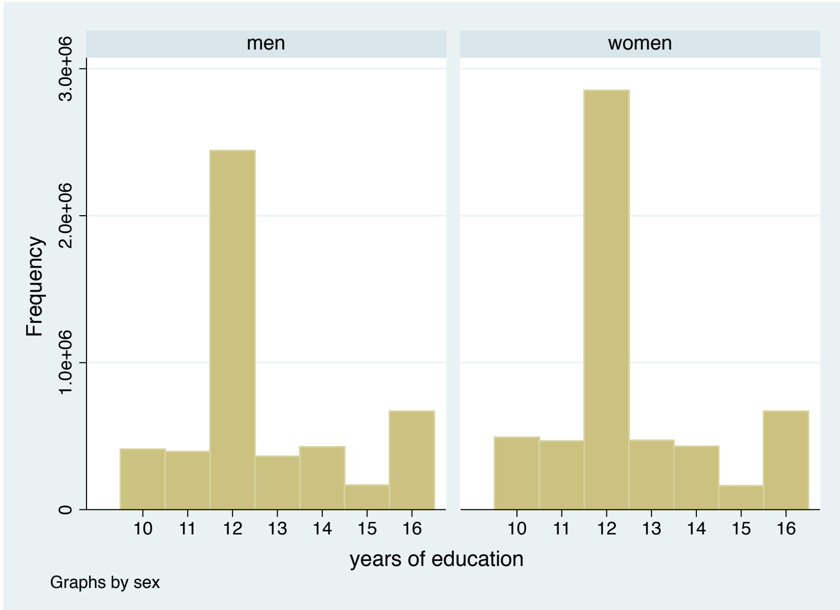
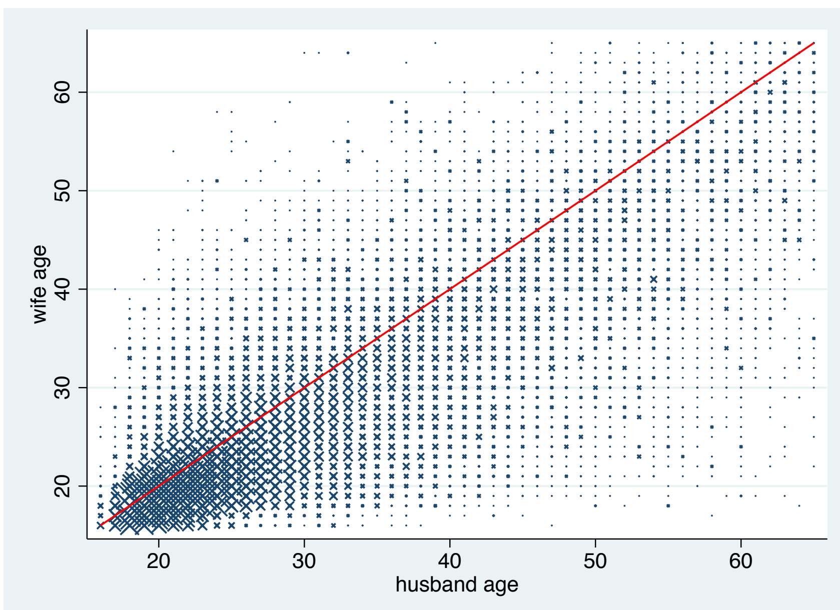


Figure 10: Pattern of marriages by age of couple.

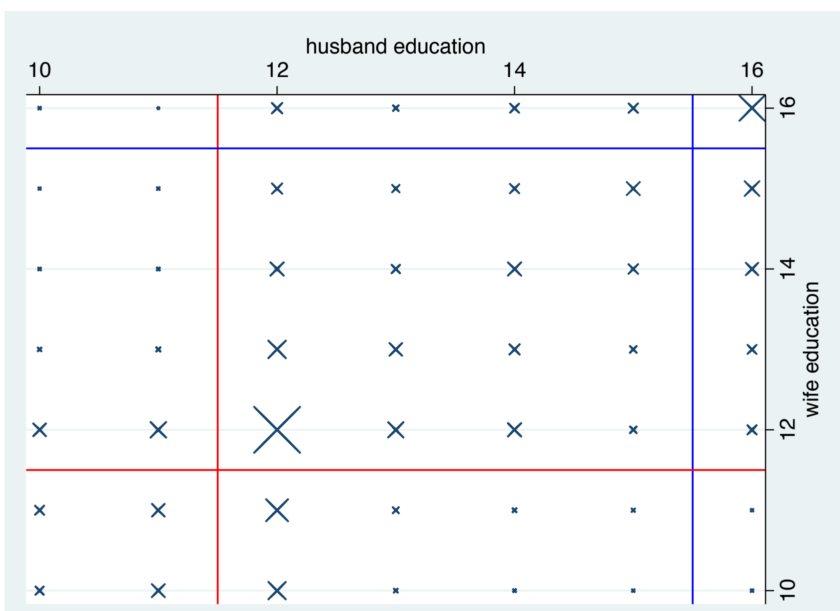


are placed between 11 and 12 years of education, therefore for markers on the right (above) of the line the husband (wife) has a high school degree. Blue lines are placed between 15 and 16 years of education, and for markers to the right (above) of it the husband (wife) has a college degree. This graph shows that there is also assortative matching on years of

Table 4: Marriages by age of couple.

	husband age										
wife age	16-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-65	Total
16-19	28,050	53,381	8,325	1,702	426	118	12	13	15	9	92,051
	7.31	13.91	2.17	0.44	0.11	0.03	0.00	0.00	0.00	0.00	23.98
20-24	6,938	90,866	43,457	11,749	2,977	839	226	84	55	23	157,214
	1.81	23.67	11.32	3.06	0.78	0.22	0.06	0.02	0.01	0.01	40.96
25-29	622	12,737	28,697	15,763	5,670	1,938	630	210	64	19	66,350
	0.16	3.32	7.48	4.11	1.48	0.50	0.16	0.05	0.02	0.00	17.28
30-34	176	2,334	6,832	10,574	6,623	3,024	1,348	499	131	69	31,610
	0.05	0.61	1.78	2.75	1.73	0.79	0.35	0.13	0.03	0.02	8.23
35-39	45	439	1,380	2,853	4,729	3,436	1,688	954	311	101	15,936
	0.01	0.11	0.36	0.74	1.23	0.90	0.44	0.25	0.08	0.03	4.15
40-44	2	115	273	840	1,391	2,201	2,200	1,343	534	136	9,035
	0.00	0.03	0.07	0.22	0.36	0.57	0.57	0.35	0.14	0.04	2.35
45-49	0	20	78	152	362	876	1,575	1,343	707	448	5,561
	0.00	0.01	0.02	0.04	0.09	0.23	0.41	0.35	0.18	0.12	1.45
50-54	0	18	10	41	106	242	484	925	1,024	578	3,428
	0.00	0.00	0.00	0.01	0.03	0.06	0.13	0.24	0.27	0.15	0.89
55-59	0	1	7	14	69	47	137	314	580	554	1,723
	0.00	0.00	0.00	0.00	0.02	0.01	0.04	0.08	0.15	0.14	0.45
60-65	0	0	0	8	2	9	26	123	181	613	962
	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.05	0.16	0.25
Total	35,833	159,911	89,059	43,696	22,355	12,730	8,326	5,808	3,602	2,550	383,870
	9.33	41.66	23.20	11.38	5.82	3.32	2.17	1.51	0.94	0.66	100.00

Figure 11: Pattern of marriages by education of couple.



education. More specifically we can observe that: (Ie) the largest differences in marriage patterns seem to be between high school dropouts and individuals with 13 years of education

Table 5: Marriages by education of couple.

wife education	husband education HS-	HS	C-	C	Total
HS-	19,413	31,186	6,145	955	57,699
	5.06	8.12	1.60	0.25	15.03
HS	26,186	123,692	38,091	12,464	200,433
	6.82	32.22	9.92	3.25	52.21
C-	4,865	33,053	34,621	15,525	88,064
	1.27	8.61	9.02	4.04	22.94
C	665	7,822	10,579	18,608	37,674
	0.17	2.04	2.76	4.85	9.81
Total	51,129	195,753	89,436	47,552	383,870
	13.32	50.99	23.30	12.39	100.00

or more; (IIe) individuals with high school degrees (college degrees) are more likely to marry partners with a high school degree (college degree) than anyone else; (IIIe) these seems to be symmetric for both men and women; and (IVe) while individuals with college degree are more likely to marry partners also with a college degree, this propensity is larger for women than for men (in other words, women with a college degree are more likely to marry partners with a college degree than men with college degree marry partners with college degree). This implies that partners with different education levels must have smaller gains from marriage than partners of similar education levels, especially when one of the partners has a high school degree and the other does not. There are not many marriages with partners of different race. Table 11, as before, presents the same information in tabular form. HS- and C- indicates non-completion of high school and college, HS and C indicates completion of high school and college degrees, respectively.

In the next section I describe the structural model.

3 The Model

In this section I first describe it and then go into more detail in the subsections below. The model consists of two stages. In the first stage individuals make decisions of whether or not to acquire one more year of education while anticipating the future payoffs to their education in both the labor and marriage markets. Individuals move forward to the marriage market in the second stage of the model after they stop acquiring education, or after reaching a maximum number of years of education. Allowing individuals to choose their level of education before marriage endogenizes education in a matching framework. The second stage of the model is a dynamic empirical equilibrium matching framework as in Choo (2015), but in which individuals marry on the basis of preferences for partner types, where potential partners are characterized by their age, educational attainment, and race. Divorce is exogenous and after a divorce, both individuals re-enter the marriage market as singles. This framework allows me to estimate preferences for partner types, and the effect of marriage market prospects on educational decisions.

3.1 First Stage

This stage is a standard application of Rust (1994). Time is discrete, and each individual lives for Z periods. For the first K periods of life, individuals choose between acquiring one more year of education or not. If the individual chooses not to continue his or her education then he or she goes to the marriage market immediately. Once in the marriage market, individuals are assumed to work earning a draw from the prevailing distribution of wages for their type, where types are defined by age, years of education and race. Individuals with K years of education go to the marriage market in period $K + 1$. The implicit assumption in this setting is that individuals complete their desired education level in a contiguous manner and that there is no further accumulation of education afterwards.

If the individual chooses to acquire one more year of education, he obtains utility $\widetilde{v}^1(i_a, i_e, i_r)+\epsilon^1_{i_a,i_e,i_r,g}(1)$, where i_e is accumulated education and i_a is age in years, i_r is race, and g indexes the male. Alternatively, an individual may choose to terminate his education in a given period, in which case he obtains utility $\epsilon^1_{i_a,i_e,i_r,g}(0)$ and goes to the marriage market. Let $e = 1$ if the individual decides to engage in education and $e = 0$ otherwise. Then the flow utility for a i_a years old male g with i_e years of accumulated education in the first stage is:

$$v^1(e, i_a, i_e, i_r, \epsilon_g) = \begin{cases} v^1(i_a, i_e, i_r) + \epsilon^1_{i_a,i_e,i_r,g}(1) & \text{if } e = 1 \\ \epsilon^1_{i_a,i_e,i_r,g}(0) & \text{if } e = 0. \end{cases} \quad (1)$$

Similarly, for a j_a years old female h with j_e years of accumulated education and race j_r, the flow utility in the first stage is:

$$w^1(e, j_a, j_e, j_r, \epsilon_h) = \begin{cases} w^1(j_a, j_e, j_r) + \epsilon^1_{j_a,j_e,j_r,h}(1) & \text{if } e = 1 \\ \epsilon^1_{j_a,j_e,j_r,h}(0) & \text{if } e = 0. \end{cases} \quad (2)$$

Where ϵ^1_g, ϵ^1_h are iid Type I Extreme Value idiosyncratic shocks that represent state variables that are observed by the decision-makers but not by the researcher.

At this point it is worth to simplify the notation a bit. Notice that an individual's type is determined by his or her age accumulated education and race. In what follows, I will denote age-education-race types for men as $i = (i_a, i_e, i_r)$ and age-education-race types for women as $j = (j_a, j_e, j_r)$.

The decision process of individuals in the first stage can be characterized by Bellman equations for their educational choices. The Bellman equation for a type i man in the first stage is:

$$
\begin{aligned}
& V^1(i,\epsilon^1_{ig}) = \\
\max & \Big\{ v^1(1,i,\epsilon^1_{ig}) + \beta\,\mathbb{E}\left[V^1(i_a+1, i_e+1, i_r, \epsilon^1_{i+1g})\right], \\
& v^1(0,i,\epsilon^1_{ig}) + V(i,\epsilon_{ig})\Big\} \qquad\qquad \text{if } i_a < K, \\
& V^1(i,\epsilon^1_{ig}) = V(i_a, K, i_r, \epsilon_{ig}) \qquad\qquad\qquad\qquad \text{if } i_a = K.
\end{aligned}
$$

Where V^1 denotes the value function in the first stage, V the value function in the second stage, and β is the discount rate. Notice how in the expression above an individual switches from the first stage to the second by choosing not to continue his education or when $i_a = K$.

The Bellman equation for a type j woman is:

$$
\begin{aligned}
& W^1(j,\epsilon^1_{jh}) = \\
\max & \Big\{ w^1(1,j,\epsilon^e_{jh}) + \beta\,\mathbb{E}\left[W^1(j_a+1, j_e+1, j_r, \epsilon^1_{jh})\right], \\
& w^1(0,j,\epsilon^1_{jh}) + W(j,\epsilon_{jh})\Big\} \qquad\qquad \text{if } j_a < K, \\
& W^1(j,\epsilon^1_{jh}) = W(j_a, K, j_r, \epsilon_{jh}) \qquad\qquad\qquad\qquad \text{if } j_a = K.
\end{aligned}
$$

Here, W^1 denotes the value function in the first stage and W the value function in the second stage. The first stage value functions for men and women in period K are identical to their value functions in the second stage.

3.2 Second Stage

The second stage of the model is a matching equilibrium framework with transferable utility as in Choo (2015), but in which partners marry on the basis of age, years of education and race. I sketch the framework next.

3.3 The Model of Marriage

Time is discrete, and each individual lives for Z periods. Let $\Omega = \{(i_a, i_e, i_r) : i_a \in \mathcal{A}, i_e \in \mathcal{E}, i_r \in \{1, 2, 3\}$ such that $i_a - i_e > 5\}$; where $\mathcal{A} = \{16, \ldots, Z\}$ is the set of possible partner ages and $\mathcal{E} = \{1, \ldots, K\}$ is the set of possible years of education. $i \in \Omega$ denotes men's types and $j \in \Omega$ denotes women's types. Single individuals in the marriage market must decide whether to remain single or to marry. If they decide to marry, they must choose which type of partner they will marry. In the second stage education is fixed at the level attained in the first stage. Then, without ambiguity, let $i + 1, j + 1$ denote one more year of age in the second stage. Let the decision to stay single be denoted with 0.

Let α_{ijk} (γ_{ijk}) be the kth period within-marriage utility for a type i man (type j woman) married to a type j woman (type i man); τ_{ij} be the amount of utility that a man of type i has to transfer to a woman of type j in order for the (i, j) match to occur, this quantity (while unobservable) is determined in equilibrium. In addition, let $T(i, j) = Z - \max(i_a, j_a) + 1$ be the maximum marriage duration that ends with the death of the older spouse.

For a type i single man g choosing alternative d_{ig}, the flow utility is:

$$v(d_{ig}, i, \varepsilon_{ig}) = v_d(i) + \varepsilon_{idg},$$

Where

$$v_d(i) = \begin{cases} \alpha_i(j) - \tau_{ij} & \text{if } d = j \in \Omega, \\ \alpha_{i0} & \text{if } d = 0, \end{cases} \tag{3}$$

and $\alpha_j(i) = \sum_{k=1}^{T(i,j)} (\beta(1 - \delta))^{k-1} \alpha_{ijk}$.

Similarly, the flow utility for a type j single woman h choosing alternative d_{jh} is:

$$w(d_{jh}, j, \varepsilon_{jh}) = w_d(j) + \varepsilon_{jdh},$$

Where

$$w_d(j) = \begin{cases} \gamma_j(i) + \tau_{ij} & \text{if } d = i \in \Omega, \\ \alpha_{0j} & \text{if } d = 0 \end{cases} \tag{4}$$

and $\gamma_i(j) = \sum_{k=1}^{T(i,j)} (\beta(1-\delta))^{k-1} \gamma_{ijk}$.

Partners utility functions satisfy two assumptions. These assumptions, introduced by (Rust, 1994), are standard in the literature of dynamic discrete choice models (Choo, 2015).

Assumption 3.1. *AS – Additive Separability: The utility functions $v(a_{i,g}, i, \varepsilon_{i,g})$ and $w(a_{j,h}, j, \varepsilon_{j,h})$ have additive separable compositions of the form*

$$v(a_{i,g}, i, \varepsilon_{i,g}) = v_a(i) + \varepsilon_{i,a,g},$$
$$w(a_{j,h}, j, \varepsilon_{j,h}) = w_a(j) + \varepsilon_{j,a,h},$$

where $\varepsilon_{i,a,g}$ and $\varepsilon_{j,a,h}$ are the ath component of the vector $\varepsilon_{i,g}$ and $\varepsilon j, h$, respectively. $v_a(i)$ and $w_a(j)$ are the mean utilities for men and women of type i, j.

Assumption 3.2. *CI – Conditional Independence: The transition probabilities of the state variables for males and females can be decomposed as*

$$\Pr(i', \varepsilon'_{i,g} \mid i, \varepsilon, a) = \mathfrak{f}(\varepsilon' \mid i)\mathcal{F}_a(i' \mid i),$$
$$\Pr(j', \varepsilon'_{j,h} \mid j, \varepsilon, a) = \mathfrak{f}(\varepsilon' \mid j)\mathcal{R}_a(j' \mid j),$$

where $\mathfrak{f}(\varepsilon)$ is the multivariate pdf of the iid ε, and $\mathcal{F}$, $\mathcal{R}$ is the probability that the man, woman of type i,j will be next single again at state i',j' given action a and state i,j.

For a type i single man, the Bellman equation is:

$$V(i, \varepsilon_{ig}) = \max \Bigg\{ \alpha_{i0} + \varepsilon_{i0g} + \beta \, \mathbb{E}\left[V_\alpha(i_a + 1, i_e, i_r, \varepsilon_{i+1g}) | i, \varepsilon_{ig}, d_{ig} = 0\right], \\ \max_{d \in \Omega} \left\{ \alpha_i(d) - \tau_{id} + \varepsilon_{idg} + \sum_{k=i_a+1}^{\min(Z, i_a + T(i,d))} \beta^{k-i_a} \, \mathbb{E}\left[V_\alpha(k, i_e, i_r, \varepsilon_{kg}) | i, \varepsilon_{ig}, d\right] \right\} \Bigg\}. \tag{5}$$

Similarly, for a type j single woman, the Bellman equation is:

$$W(j, \varepsilon_{jh}) = \max \Bigg\{ \gamma_{j0} + \varepsilon_{j0h} + \beta \, \mathbb{E}\left[W_\gamma(j_a + 1, j_e, j_r, \varepsilon_{j+1h}) | j, \varepsilon_{jh}, d_{jh} = 0\right], \\ \max_{d \in \Omega} \left\{ \gamma_j(d) + \tau_{dj} + \varepsilon_{jdh} + \sum_{k=j_a+1}^{\min(Z, j_a + T(d,j))} \beta^{k-j_a} \, \mathbb{E}\left[W(k, j_e, j_r, \varepsilon_{kh}) | j, \varepsilon_{jg}, d\right] \right\} \Bigg\}. \tag{6}$$

For both men and women, ε denotes an unobserved state variable observed by the agents but not the researchers. Under the assumption that ε follows a Type I Extreme Value distribution, the conditional choice probabilities of a type i man (type j woman) choosing to marry a type j woman (type i man) are:

$$\mathcal{P}_{ij} = \frac{\exp(\widetilde{v}_{ij} - \widetilde{v}_{i0})}{1 + \sum_{d \in \Omega} \exp(\widetilde{v}_{id} - \widetilde{v}_{i0})} \\ \left(\mathcal{Q}_{ij} = \frac{\exp(\widetilde{w}_{ij} - \widetilde{w}_{0j})}{1 + \sum_{d \in \Omega} \exp(\widetilde{w}_{dj} - \widetilde{w}_{0j})} \right).$$

Where $\widetilde{v}, \widetilde{w}$ denote the mean component of the value functions for single men and women:

$$\widetilde{v}_{ij} = \begin{cases} \alpha_i(j) - \tau_{ij} + \sum_{k=i_a+1}^{\min(Z, i_a+T(i,j))} \beta^{k-i_a} \mathbb{E}\left[V(k, i_e, i_r, \varepsilon_{kg}) | i, \varepsilon_{ig}, j\right], & \text{if } i_a < Z, j \neq 0, \\ \alpha_{i0} + \beta \, \mathbb{E}\left[V_\alpha(i_a+1, i_e, i_r, \varepsilon_{i+1g}) | i, \varepsilon_{ig}, 0\right], & \text{if } i_a < Z, j = 0, \\ (\alpha_i(j) - \tau_{ij}) \, \mathbb{1}(j \neq 0) + \alpha_{0i} \mathbb{1}(j = 0), & \text{if } i_a = Z. \end{cases} \tag{7}$$

$$\widetilde{w}_{ij} = \begin{cases} \gamma_j(i) + \tau_{ij} + \sum_{k=j_a+1}^{\min(Z, j_a+T(i,j))} \beta^{k-j_a} \mathbb{E}\left[W(k, j_e, j_r, \varepsilon_{kh}) | j, \varepsilon_{jh}, i\right], & \text{if } j_a < Z, i \neq 0, \\ \gamma_{0j} + \beta \, \mathbb{E}\left[W(j_a+1, j_e, j_r, \varepsilon_{j+1h}) | j, \varepsilon_{jh}, 0\right], & \text{if } j_a < Z, i = 0, \\ (\gamma_j(i) + \tau_{ij}) \, \mathbb{1}(i \neq 0) + \gamma_{j0} \mathbb{1}(i = 0), & \text{if } j_a = Z. \end{cases} \tag{8}$$

3.3.1 The Marriage Market Equilibrium

Let $m = (m_i)_{i \in \Omega}$, $f = (f_j)_{j \in \Omega}$ denote the vectors of available men and women, where Ω is the set of possible types. Each of these vector records of the number of single men and women of each type $i, j \in \Omega$ participating in the second stage. Let $\mu = (\mu_{ij})_{i,j \in \Omega}$, $\tau = (\tau_{ij})_{i,j \in \Omega}$ be the vectors of matches and transfers. These vectors are composed of the number of matches between types of men and women and their transfers. We can now define a marriage market equilibrium as in Choo (2015):

Definition 3.1. *Choo, 2015. A marriage market equilibrium consists of a vector of available men m, and women f, the vector of marriages μ and the vector of transfers τ such that the number of type i men who want to marry type j spouses equals the number of type j women who want to marry type i men for all combinations $i, j \in \Omega$. That is, for each of the $|\Omega| \times |\Omega|$ sub-markets*

$$m_i \mathcal{P}_{ij} = f_j \mathcal{Q}_{ij} = \mu_{ij}.$$

Using the definition above, Choo (2015) derives the Dynamic Marriage Matching Function for a (i,j) marriage:

$$\mu_{ij} = \Pi_{ij}\sqrt{m_i f_j}\prod_{k=0}^{T(i,j)-1}\left(\frac{\mu_{i+k,0}\mu_{0,j+k}}{m_{i+k}f_{j+k}}\right)^{1/2(\beta(1-\delta))^k}, \tag{9}$$

where $\log\Pi_{ij} = \frac{1}{2}(\alpha_i(j) + \gamma_j(i) - \alpha_{i0}(j) - \gamma_{0j}(i)) - \kappa$, and κ is a geometric sum of Euler's constants $\kappa = c\beta(1-\delta)(1-(\beta(1-\delta))^{T(i,j)})/(1-\beta(1-\delta))$. That is, $\widehat{\Pi}_{ij}$ identifies the marriage gains relative to remaining single for the duration of the match.

This dynamic marriage matching function must also satisfy the following accounting constraints.

$$\mu_{i0} + \sum_{j\in\Omega}\mu_{ij} = m_i, \quad \forall i\in\Omega; \tag{10}$$

$$\mu_{0j} + \sum_{i\in\Omega}\mu_{ij} = f_j, \quad \forall j\in\Omega; \tag{11}$$

$$\mu_{0j}, \mu_{i0}, \mu_{ij} \geq 0, \quad \forall i,j\in\Omega. \tag{12}$$

Notice that the total number of individuals interacting in the second stage of the model is

$$N_p = \sum_{i\in\Omega} m_i + \sum_{j\in\Omega} f_j = \sum_{i\in\Omega}\mu_{i,0} + \sum_{j\in\Omega}\mu_{0,j} + 2\sum_{i\in\Omega}\sum_{j\in\Omega}\mu_{i,j}, \tag{13}$$

and the total number of households formed according to the model (assuming that single individuals form independent households) is

$$N_H = \sum_{i\in\Omega}\mu_{i,0} + \sum_{j\in\Omega}\mu_{0,j} + \sum_{i\in\Omega}\sum_{j\in\Omega}\mu_{i,j} = N_p - \sum_{i\in\Omega}\sum_{j\in\Omega}\mu_{i,j}. \tag{14}$$

The first equation serves to validate the counterfactual exercises below; while the second equation provides the number of households for which to calculate inequality in the counterfactuals.

Summarizing, single individuals make decisions of whether to marry or not. If they decide to marry, they choose what type of partner to marry – types are differentiated by age, years of education and race. Marriage "locks" individuals into a flow of utilities within marriage until the marriage is dissolved. The utilities within marriage vary by the individuals' own type and the spouse's type. A marriage can be dissolved by divorce or death of the spouse. After a divorce, both individuals re-enter the marriage market as singles. When making marital decisions, individuals hold rational expectations about the future value of participating in the marriage market after the match dissolves. In equilibrium, the number of women of type j choosing to marry men of type i is equal to the number of men of type i choosing to marry women of type j.

Let $\mathbf{V}_i = \int V(i, \varepsilon_g)\mathfrak{f}(\varepsilon_g)\, d\varepsilon_g$ and $\mathbf{W}_j = \int W(j, \varepsilon_h)\mathfrak{f}(\varepsilon_h)\, d\varepsilon_h$ be the integrated value functions for the decisions to marry or stay single for men and women respectively. Under the assumption of Type I Extreme Value distribution of ε, Choo (2015) shows that

$$\mathbf{V}_i = \begin{cases} \alpha_{i0} + c - \log \mathcal{P}_{i0} + \mathbf{V}_{i+1}, & \text{if } i < Z, \\ \alpha_{i0} + c - \log \mathcal{P}_{i0}, & \text{if } i = Z. \end{cases} \tag{15}$$

$$\mathbf{W}_j = \begin{cases} \gamma_{0j} + c - \log \mathcal{Q}_{0j} + \mathbf{W}_{j+1}, & \text{if } j < Z, \\ \gamma_{0j} + c - \log \mathcal{Q}_{0j}, & \text{if } j = Z. \end{cases} \tag{16}$$

Where $c = 0.57721\ldots$ is Euler's constant. These expressions for the integrated value functions are used to link the second stage to the first stage when individuals make their educational decisions.

3.4 Identification

Under the assumption of conditional independence in Rust (1994), the conditional probabilities of educational choices of men can be consistently estimated from the data on individual's decisions to continue or not their educational accumulation given ages, cumulative education and race. Using these conditional choice probabilities – and under the Type I Extreme value distribution of the unobservable –, I can obtain the choice-specific value functions using the Hotz-Miller inversion (Hotz and Miller, 1993). Then, the variation in educational choices of men with different age, cumulative education and race identify the parameters the flow utility for educational decisions of men.[16] With a similar argument, it can be shown that parameters in the utility of women in the fist stage are identified.

In the second stage, with assumption 3.2, the conditional choice probabilities at a point in time can be identified from the marital choices of men and women of different type observed in the data. Given stationarity of the population of men and women, and given the divorce rate δ and the time discount factor β, these probabilities are also the conditional choice probabilities of marital choices of men and women in future ages. The conditional choice probabilities identify the value function for different types of men and women (Arcidiacono and Miller, 2011). In particular, the value function for different types of men and women can be expressed solely as function of the probabilities of marriage. Summing the value functions for men and women then identifies the gains from marriage (Chen, 2016).[17]

Moreover, Chen (2016) demonstrates that under mild conditions on the model primitives, the marriage market equilibrium in Choo (2015) (Definition 3.1) is unique. His proof relies on a new fixed-point representation that the equilibrium conditional choice probabilities must satisfy. The uniqueness of the equilibrium allows for a unique predicted distribution of matches when conducting counterfactual exercises.

[16]The result in (Hotz and Miller, 1993) is independent of the parameterization of the flow utility.

[17]Chen (2016) results on identification can be applied to a large class of distribution of unobserved heterogeneity.

4 Estimation

Suppose we observe data on matches $\breve{\mu}_{ij}$, available single men $\breve{m}_i$ and available single women $\breve{f}_j$. Then, in the second stage Π_{ij} can be estimated from the expression of the marriage matching function:

$$\widehat{\Pi}_{ij} = \breve{\mu}_{ij} \left(\sqrt{\breve{m}_i \breve{f}_j} \prod_{k=0}^{T(i,j)-1} \left(\frac{\breve{\mu}_{i+k,0} \breve{\mu}_{0,j+k}}{\breve{m}_{i+k} \breve{f}_{j+k}} \right)^{1/2(\beta(1-\delta))^k} \right)^{-1} . \tag{17}$$

I use equations 15 and 16 to solve backwards for the value functions at earlier ages for $i < K$. This allows me to obtain expressions for the conditional choice probabilities of the educational decisions (and then form the likelihood function in the first stage) while taking into account the value of education in the marriage market. In this first stage, I parameterize the flow utility for men and women as a set of dummies for age, and a set of dummies for race[18]:

$$\widetilde{v}^1(i) = \alpha_1^1 + \alpha_2^1(i_a) + \alpha_3^1(i_r). \tag{18}$$

$$\widetilde{w}^1(j) = \gamma_1^1 + \gamma_2^1(j_a) + \gamma_3^1(j_r). \tag{19}$$

The log likelihood function is:

$$\mathcal{L}(\theta) = \sum_{i,j \in \Omega} \left(\sigma_{i,1} \log(\mathcal{P}_i^1(\theta)) + \sigma_{i,0} \log(1 - \mathcal{P}_i^1(\theta)) + \varsigma_{j,0} \log(\mathcal{Q}_j^1(\theta)) + \varsigma_{j,1} \log(1 - \mathcal{Q}_j^1(\theta)) \right), \tag{20}$$

where $\mathcal{P}^1, \mathcal{Q}^1$ are the conditional choice probabilities of educational decisions for men and women in the first stage.[19] $\sigma_{i,0}, \sigma_{i,1}$ are the number of men with state vector i choosing

[18]Note that in this context, age and years of education are collinear. This is a consequence of the backtracing of educational decisions in the construction of the artificial panel. Since the assumption is that education is acquired contiguously a person that is still in school at age 18, for example, must necessarily have a high school degree (12 years of education).

[19]Under the assumptions in Rust (1994), the conditional choice probability for continuing education for man with characteristics i is

$$\mathcal{P}_i^1(\theta) = \frac{\exp(\widetilde{v}^1(i;\theta))}{1 + \exp(\widetilde{v}^1(i))},$$

to continue or stop education. $\varsigma_{j,0}, \varsigma_{j,1}$ are the number of women with state vector j choosing to continue or stop education. $\theta = (\alpha_1^1, \alpha_2^1(\cdot), \alpha_3^1(\cdot), \gamma_1^1, \gamma_2^1(\cdot), \gamma_3^1(\cdot))$ is a vector of parameters to be estimated.

The table below displays values of the fixed parameters used in the estimation.

Table 6: Fixed parameters used in estimation.

Parameter	Value
β	0.95
δ	0.05
min age	16
max age (Z)	65
min edu	10
max edu	16

5 Results

5.1 First Stage Results

This section presents the results for the estimation of the first stage, in which individuals choose education. Table 7 displays the estimated parameters of the first stage. Each coefficient represents the effect of the state variable on the probability of continuing acquiring education. The table shows that men are more likely than women to stop acquiring education after finishing high school (at age 18). However, notice the persistence of continuing education given college attendance (ages 19 to 21). This persistence is thought to arise because of self-selection into college (Bound and Turner, 2011). Also notice that race plays an important role in determining educational decisions. Black individuals are more likely to drop from continuing education at any given age. This finding is consistent with previous studies (Neal, 2006). These results are not surprising and are found in the literature, however research to understand the root causes of these observable differences in school enrolment

and similarly for women.

and completion remains to be completed (Deere and Vesovic, 2006).

Table 7: First-stage estimates.

parameter	utility of men	utility of women
constant	α_1^1: 6.0525	γ_1^1: 4.4533
	(0.0028)	(0.0042)
age = 17	$\alpha_2^1(17)$: 0.6335	$\gamma_2^1(17)$: 0.0138
	(0.0031)	(0.0066)
age = 18	$\alpha_2^1(18)$: -0.3040	$\gamma_2^1(18)$: 0.0419
	(0.0035)	(0.0050)
age = 19	$\alpha_2^1(19)$: 2.3709	$\gamma_2^1(19)$: 3.7037
	(0.0035)	(0.0056)
age = 20	$\alpha_2^1(20)$: 2.6480	$\gamma_2^1(20)$: 2.1888
	(0.0037)	(0.0055)
age = 21	$\alpha_2^1(21)$: 2.3490	$\gamma_2^1(21)$: 6.1259
	(0.0033)	(0.0046)
black	$\alpha_3^1(2)$: -1.4590	$\gamma_3^1(2)$: -2.1269
	(0.0023)	(0.0016)
other races	$\alpha_3^1(3)$: -0.9133	$\gamma_3^1(3)$: -1.7443
	(0.0076)	(0.0049)

Standard errors in parenthesis.

5.2 Second Stage Results

Each set of estimates in the second stage comprises 974,169 numbers Π_{ij}, corresponding to each of the possible types of marriage based on the types of men and women.[20]

As explained above, Π_{ij} identifies the gains from marriage relative to staying single for the length of the marriage for a couple formed by a type i man and a type j woman. Specifically,

$$\begin{aligned} \log \Pi_{ij} =& \tfrac{1}{2}\left(\alpha_i(j) + \gamma_j(i) - \alpha_{i0}(j) - \gamma_{0j}(i)\right) - \kappa = \tfrac{1}{2}(\text{gains}_{ij}) - \kappa, \\ \Rightarrow \text{gains}_{ij} =& 2\left(\log \Pi_{ij} + \kappa\right). \end{aligned} \tag{21}$$

[20]Each man or woman is characterized by their age, years of education and race: i and j. In this paper I consider individual aged between 16 and 65 with 10 to 16 years of education and white, black or other races. After eliminating impossible combinations of age and education, I end up with 987 individual types. Squaring this number yields the number of possible marriage types.

The estimated Π_{ij}, and therefore the estimated gains from marriage, vary with the 6 characteristics of a marriage (age of husband, education of husband, race of husband, age of wife, education of wife, race of wife). I use several figures to present the results. Let $\Delta education$ = education husband−education wife. Figure 12 displays the estimated average gains from marriage as a function of $\Delta education$ for marriages between partners of the same race. I weight the gains by the observed number of marriages in all figures. Figure 12 shows that the gains are larger when the partners have the same level of education. The gains are largely driven by marriages with partners of the same race, and marriages between partners of different races obtain smaller gains – see Figure 13. The decrease in gains is more symmetric as the level of education of the partners drifts apart, but the decrease is faster as the education of the individuals differ. Confidence intervals for the estimates of Π along $\Delta education$ is provided in Figure 17. Notice that the width of the intervals decreases as $\Delta education$ move away from zero. This means that the Π are more precisely estimated to be small in repeated bootstrap samples. In other words, in many bootstrap samples, there are few marriages formed when the education of the husband and the education of the wife are far apart from each other.

Figure 12: Average weighted gains along $\Delta education$.

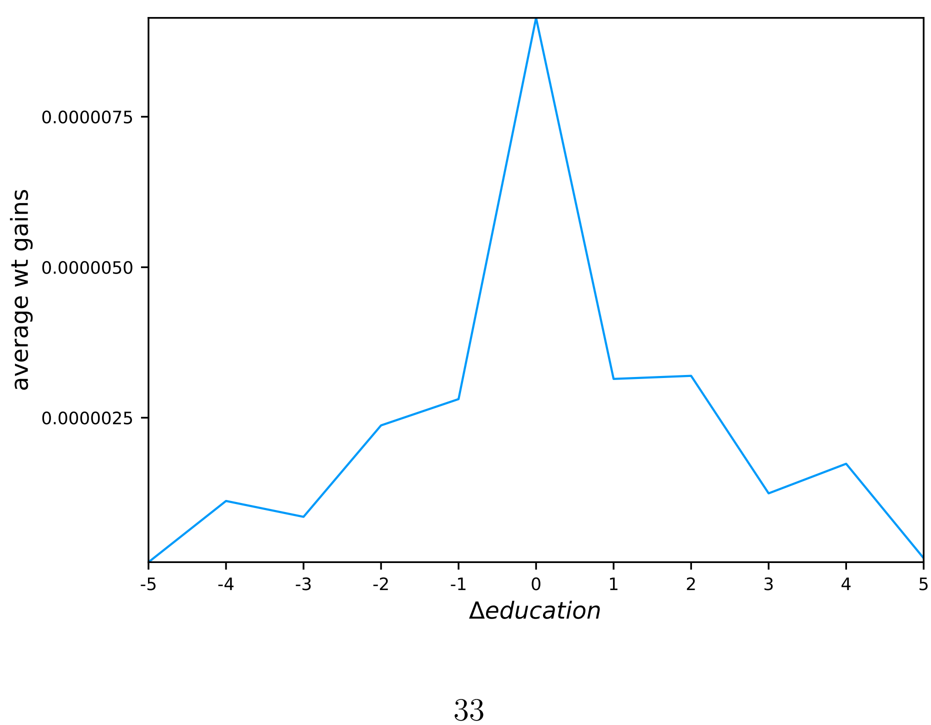


Figure 13: Average weighted gains along $\Delta education$ by race.

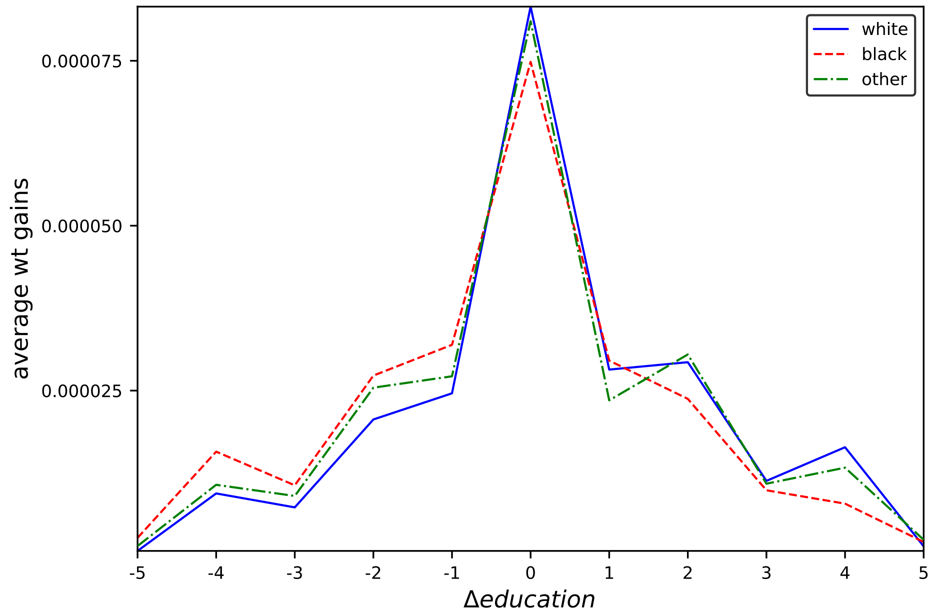


Figure 14: Average weighted gains along $\Delta education$, white husband.

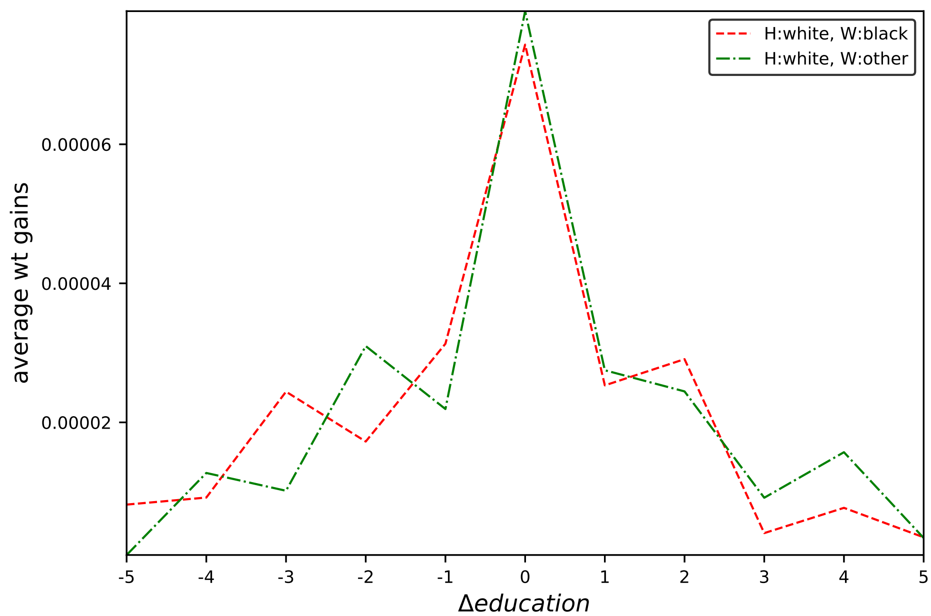


Figure 15: Average weighted gains along $\Delta education$, black husband.

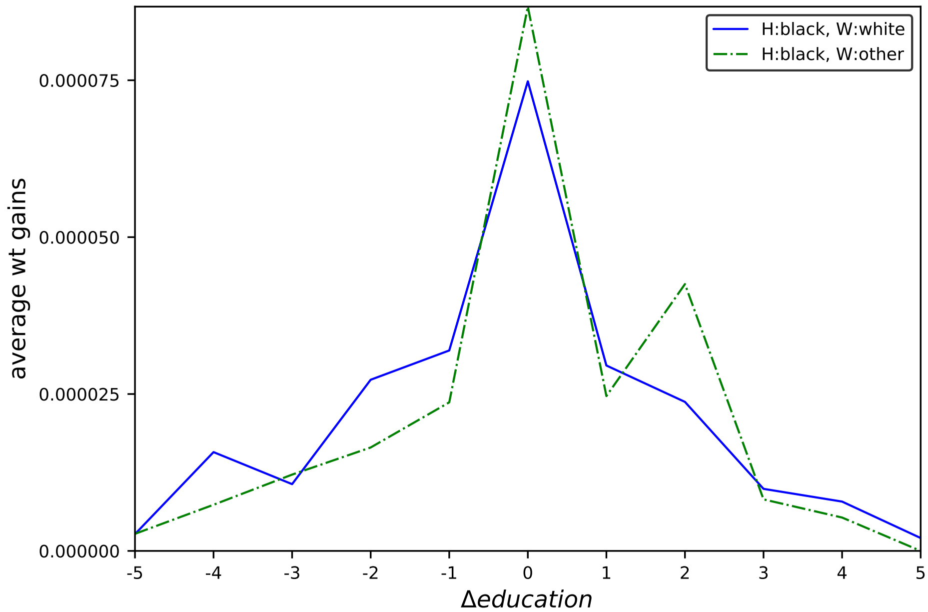


Figure 16: Average weighted gains along $\Delta education$, other husband.

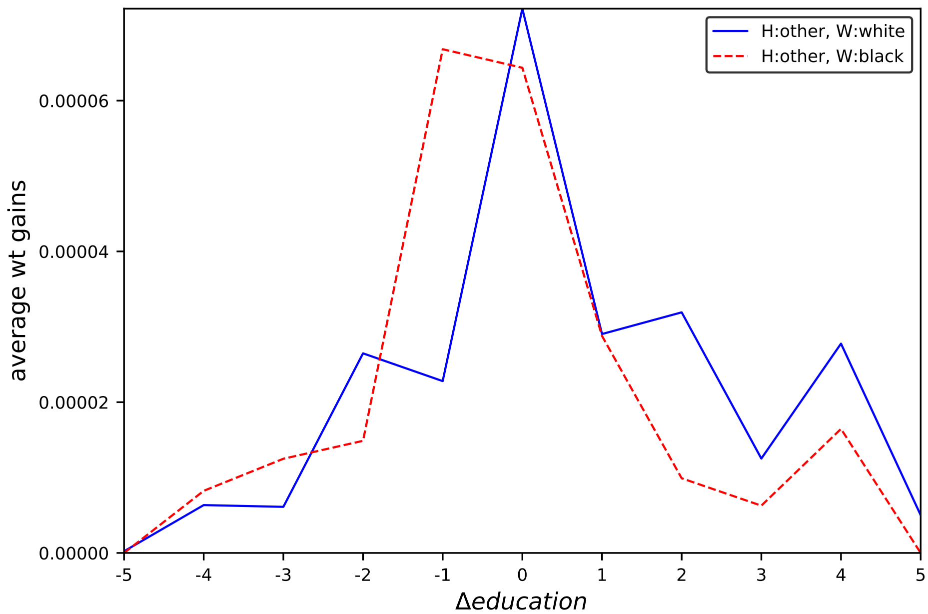
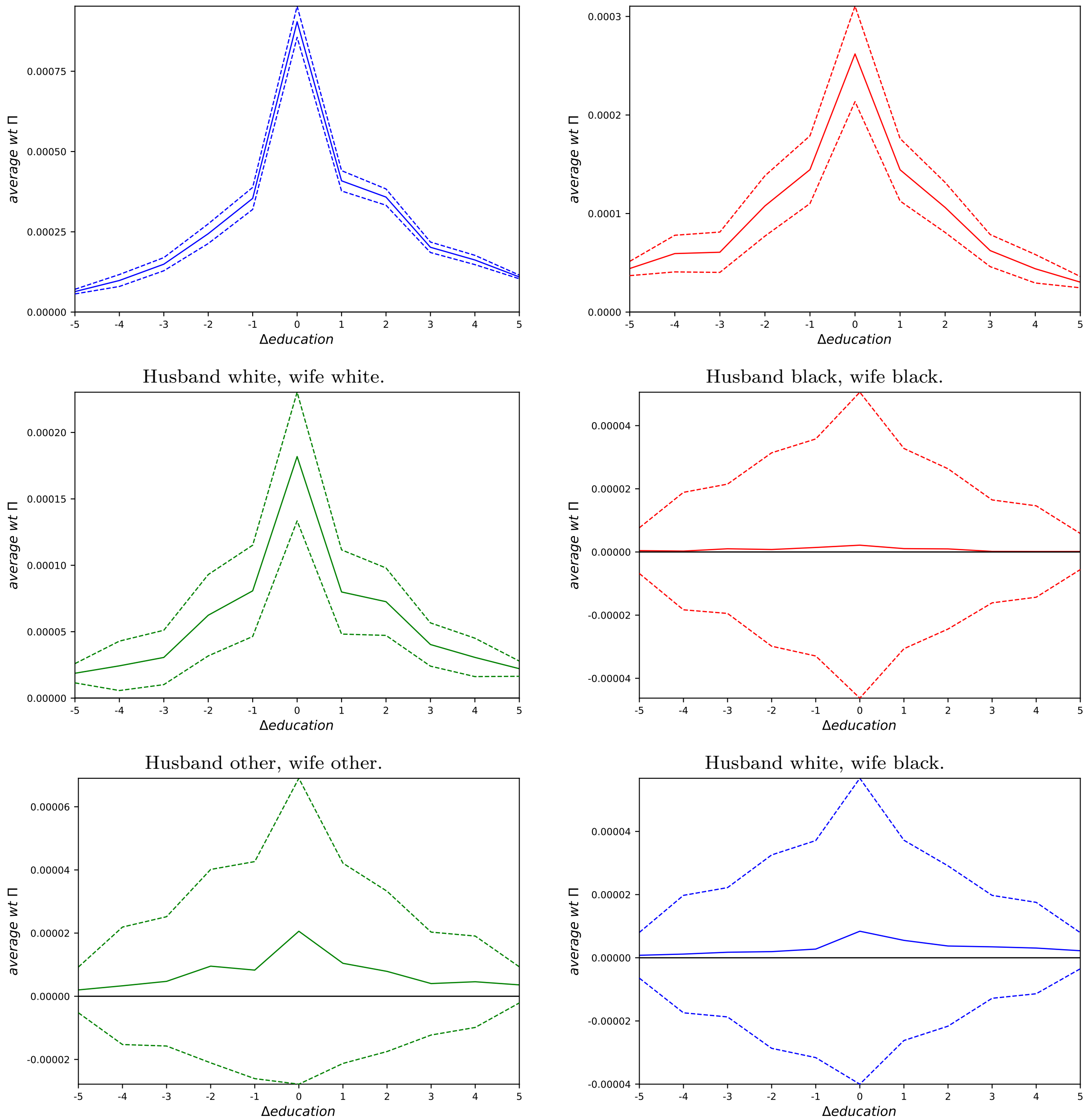


Figure 17: Average weighted estimates of Π and 95% CI along Δedu by race.



Husband white, wife white.

Husband black, wife black.

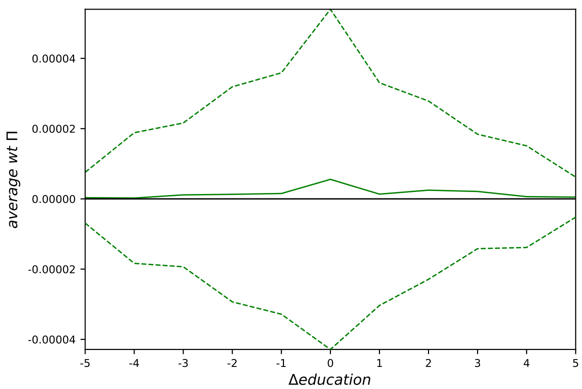
Husband other, wife other.

Husband white, wife black.

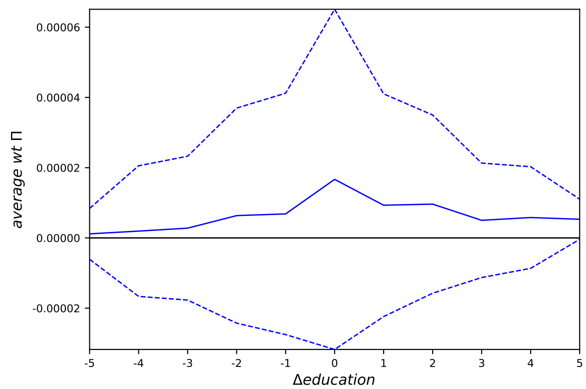
Husband white, wife other.

Husband black, wife white.

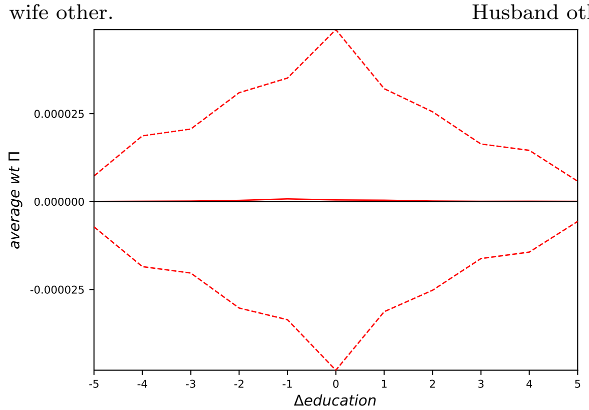
The literature identifies two main reasons why assortative matching can be generated. First, it may be that people prefer to match with partners of similar characteristics – this is called the matching hypothesis. This results in assortative matching because people will match with someone similar to themselves. Second, both men and women prefer partners



Husband black, wife other.



Husband other, wife white.



Husband other, wife black.

with better attributes – this is the competition hypothesis. This hypothesis leads to assortative matching because people will not marry down, and in equilibrium everyone ends up marrying partners similar to themselves.

In the next set of figures I examine how the gains change as function of $\Delta age =$ age husband$-$ age wife. There are large gains for partners of similar age. However, people prefer marriages in which the husband is slightly older than the wife. The gains peak when the husband is one year older than the wife and decrease as the ages of the partners grow apart. The gains decrease faster when the wife is older than the husband. Choo and Siow (2006) and Choo (2015) find similar results of sorting by age. The scale of the vertical axis in these figures gives a sense of the strength of sorting along educational lines relative to sorting along age. The gains from sorting by age are an order of magnitude larger than the gains from sorting by education. Confidence intervals for the estimates of Π are shown in figure 24. Here, the width of the intervals decreases as Δage increases, which means that the Π are precisely estimated to be small in repeated bootstrap samples. In other words, matches for which the age of the husband is much larger than the age of the wife experience small gains from marriage, but it is precisely estimated.

Figure 18: Average weighted gains along Δage.

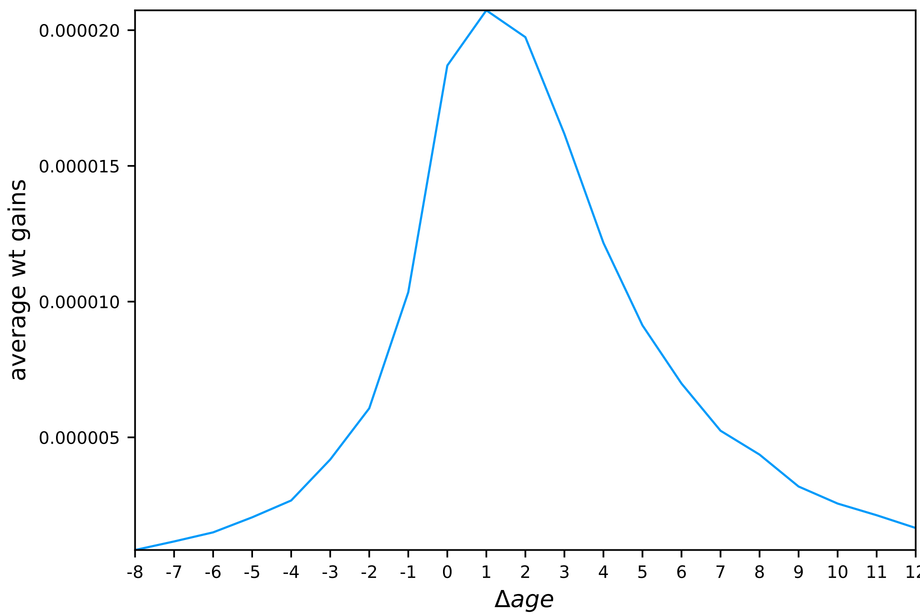


Figure 19: Average weighted estimates of Π and 95% CI along Δage.

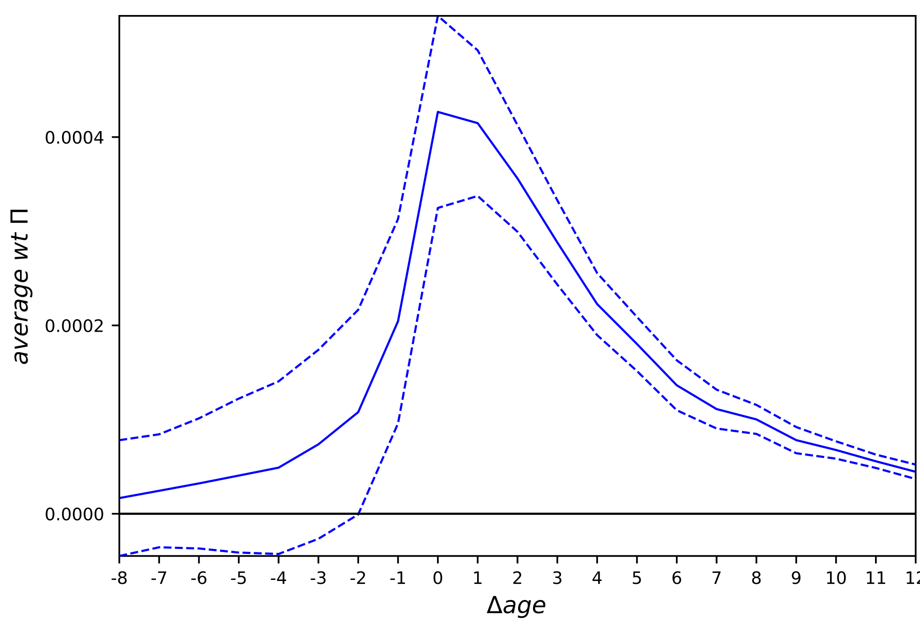


Figure 20 splits the gains by race of the partners. The large gains from marriage along Δage are mainly driven by marriages partners of the same race. Marriages between partners of different races obtain smaller gains, as depicted in figures 21, 22, and 23, even when the partners have similar age.

Figure 20: Average weighted gains along Δage by race.

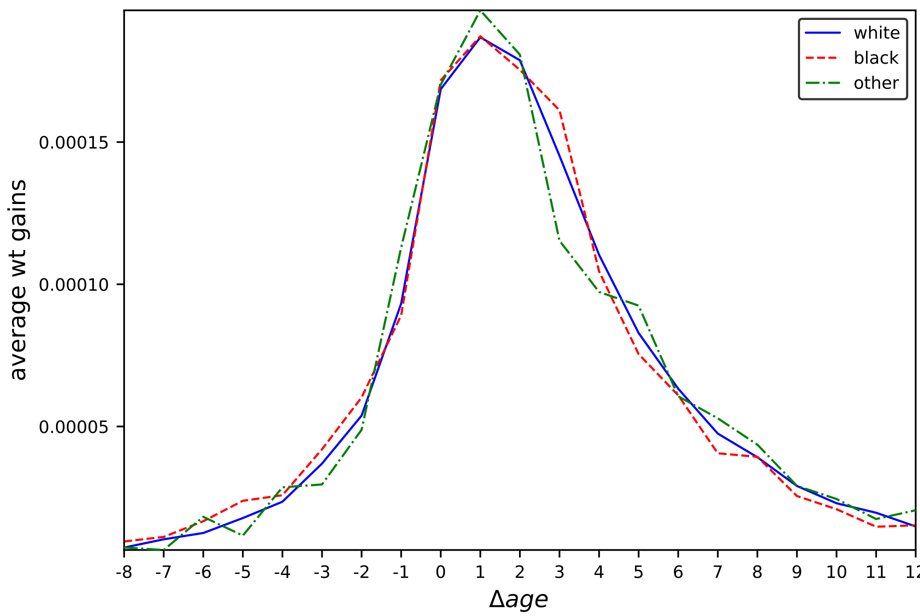


Figure 21: Average weighted gains along Δage, white husband.

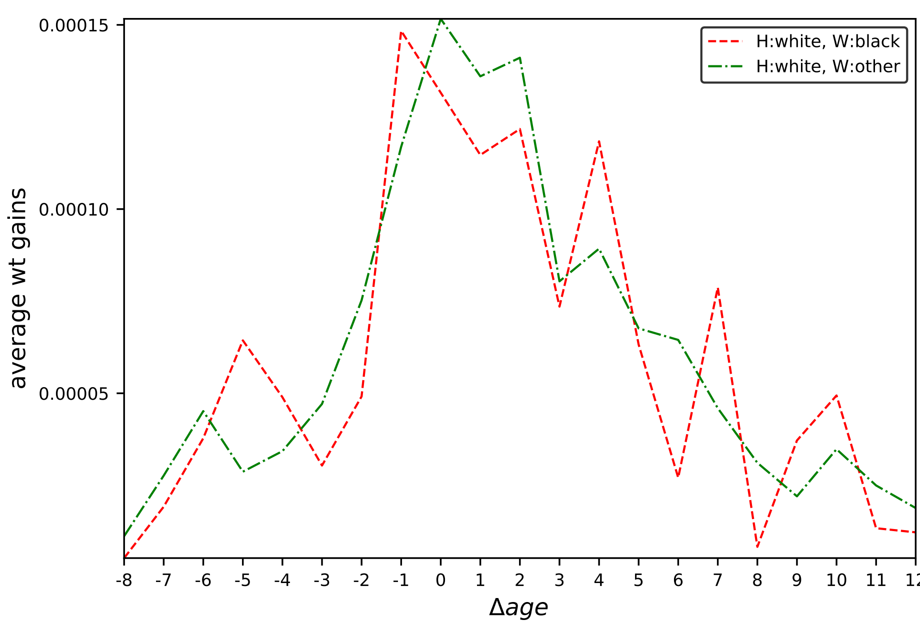


Figure 22: Average weighted gains along Δage, black husband.

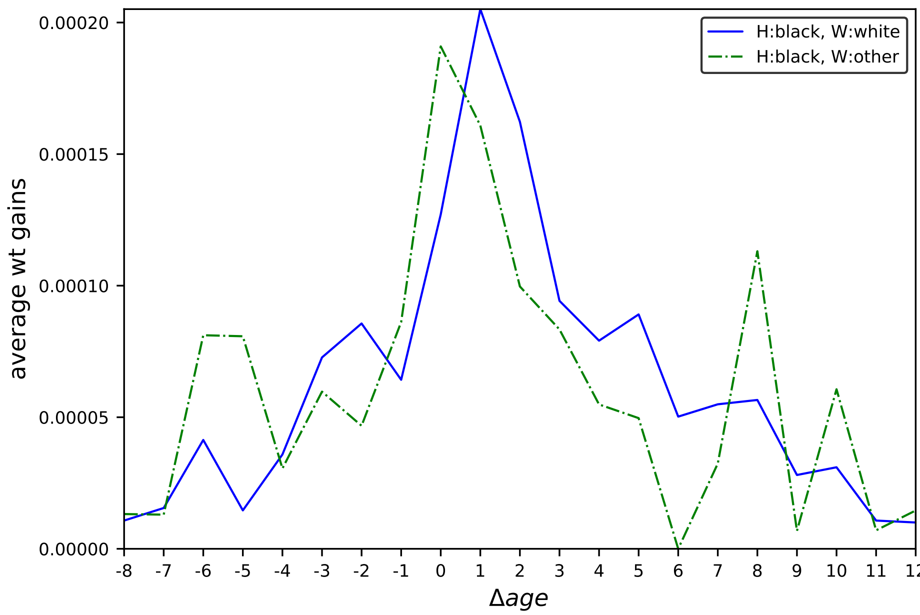


Figure 23: Average weighted gains along Δage, other husband.

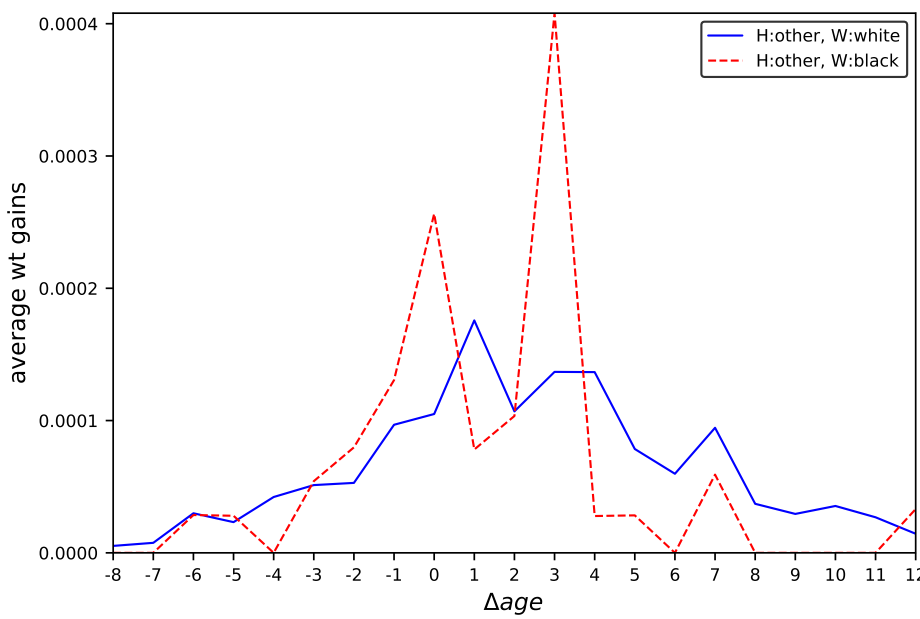
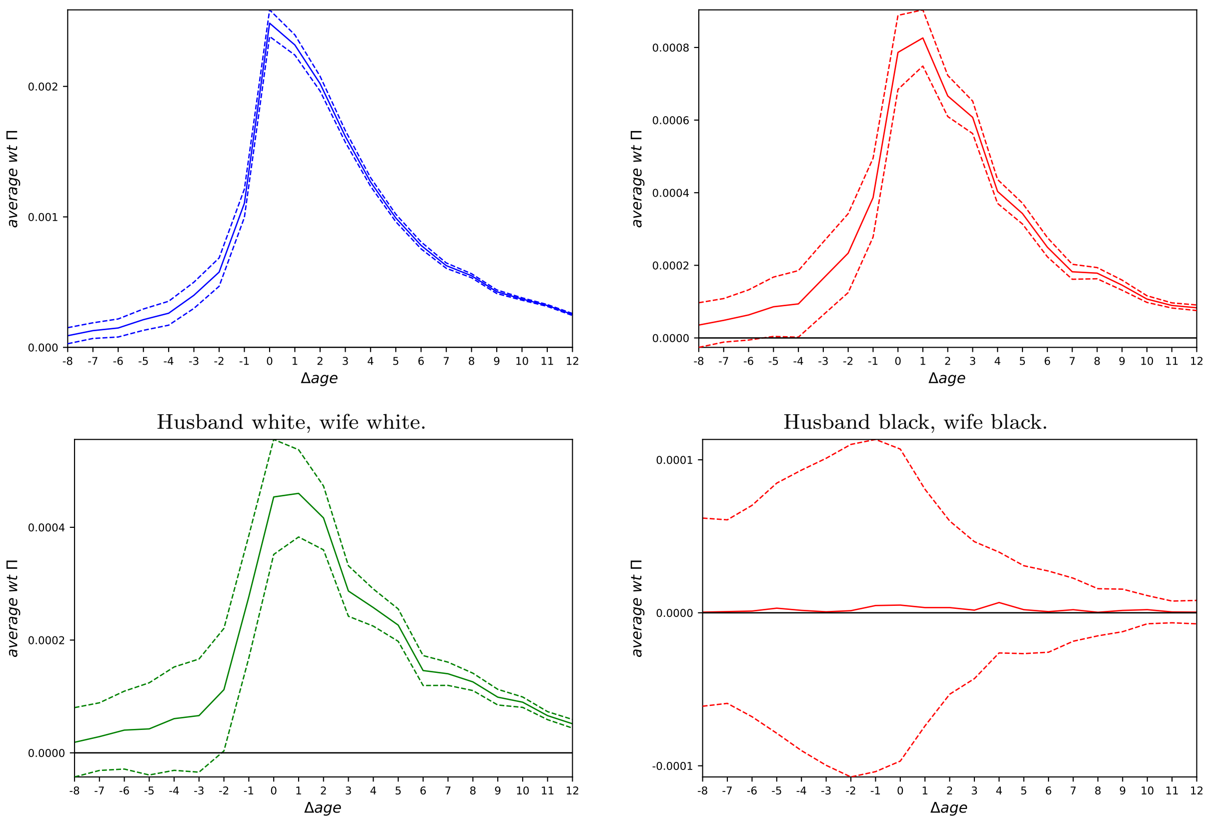


Figure 24: Average weighted estimates of Π and 95% CI along Δage by race.



Husband white, wife white.

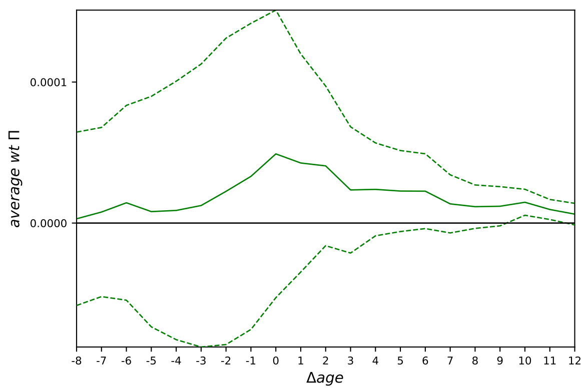
Husband black, wife black.

Husband other, wife other.

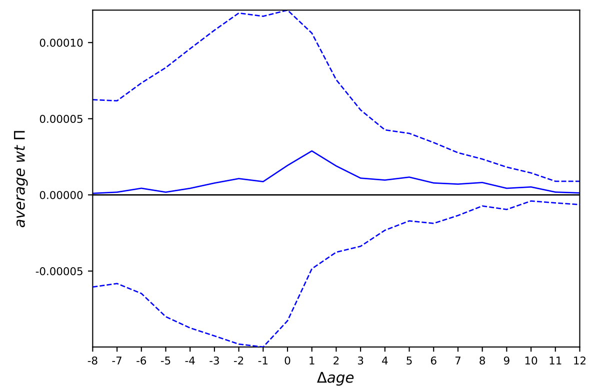
Husband white, wife black.

6 Addressing Inequality

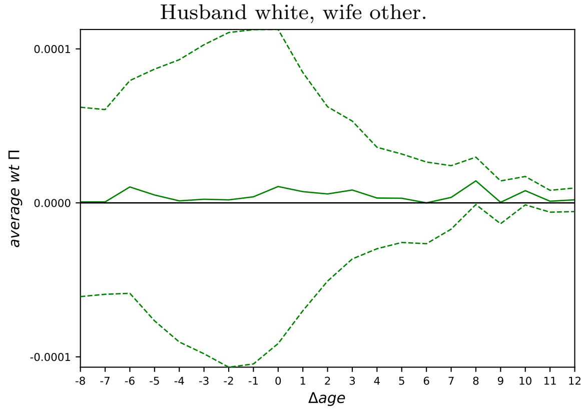
In the previous sections, I estimated a structural model to recover the gains from marriage for all different types of marriages. These gains are functions of deep parameters that capture preferences for marriage across different partner types in different within-marriage periods, preferences for staying single, and preferences for time discounting, while taking into consideration the possibility of divorce and the relative scarcity of potential partner types in the market. Holding these preferences fixed, and given counterfactual distributions of available singles types, I can obtain a resulting distribution of marriages $M \equiv (\mu_{ij})_{i,j\in\Omega}$.



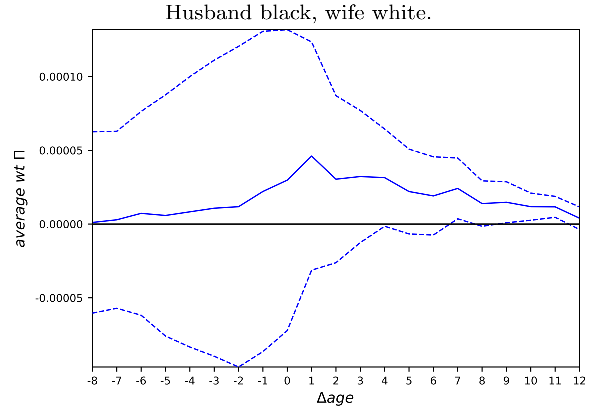
Husband white, wife other.



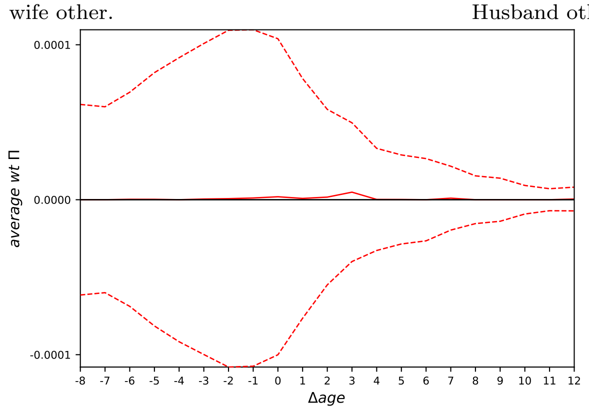
Husband black, wife white.



Husband black, wife other.



Husband other, wife white.



Husband other, wife black.

To compute the counterfactual distribution of income corresponding to a counterfactual distribution of marriages, I decompose the distribution of incomes into the distribution of marriages and the conditional distribution of income given match type. Let $M(i,j)$ be a distribution of matches (and singles), $F_{Y|i,j}$ be the distribution of household income conditional on a given match type (i,j). Then, the (unconditional) distribution of income can be decomposed as:

$$F_Y(y) = \mathbb{E}_M\left[F_{Y|i,j}(y)\right] = \int F_{Y|i,j}(y \mid i,j)\, dM(i,j)\,. \tag{22}$$

Furthermore, assuming that incomes of the wife and husband are independent after conditioning on characteristics, household income is $y_{i,j} = \omega_i + \omega_j$, with distribution $F_{Y|i,j}$.[21]

Expression 22 can also be used to construct a counterfactual distribution of income $\widehat{F}$ for a given counterfactual distribution of matches $\widehat{M}$:

$$\widehat{F}_Y(y) = \int F_{Y|i,j}(y \mid i,j)\, d\widehat{M}(i,j)\,. \tag{23}$$

Notice also that I can use any given conditional distribution of income $F_{Y|i,j}$ to construct the counterfactual distribution of incomes $\widehat{F}_Y$. This means that I can use any given "wage structure" based on observable characteristics i,j of the partners to conduct another class of counterfactual experiments by changing the wage structures. For example, I can use different observed $F_{Y|i,j}$ corresponding to different years.

After constructing the counterfactual distribution of income, I compute the Gini coefficient with the following formula (Yitzhaki and Schechtman, 2013):

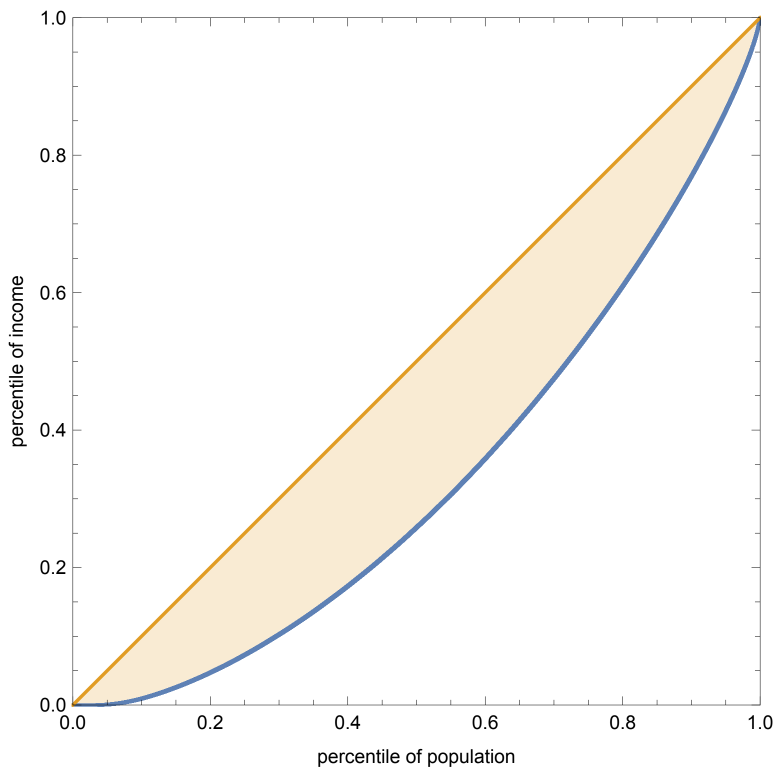
$$G = \frac{2}{\bar{y}} \sum_{i=1}^{n} p_i (y_i - \bar{y}) \left(\frac{F_Y(y_i) + F_Y(y_{i-1})}{2}\right). \tag{24}$$

[21] Under the assumption of independence of partner's incomes conditional on their own characteristics, this distribution has density $f_{Y|i,j}(y \mid i,j) = (f_{\omega_i|i} * f_{\omega_j|j})(y \mid i,j)$, where $*$ is the convolution operator.

6.1 Benchmark: Inequality in 1980

This section provides the benchmark of inequality of couples' incomes as measured by the Gini coefficient. According to data from the NCHS, there were 383,870 new marriages in the reporting states in 1980. I cannot observe couple income from the marriage certificates. Instead, I use the procedure described above to calculate the distribution of combined incomes for couples. The resulting Gini coefficient for newly married couples in 1980 is 0.332. The Lorenz curve for these incomes is shown in Figure 25 and the CDF in Figure 26.

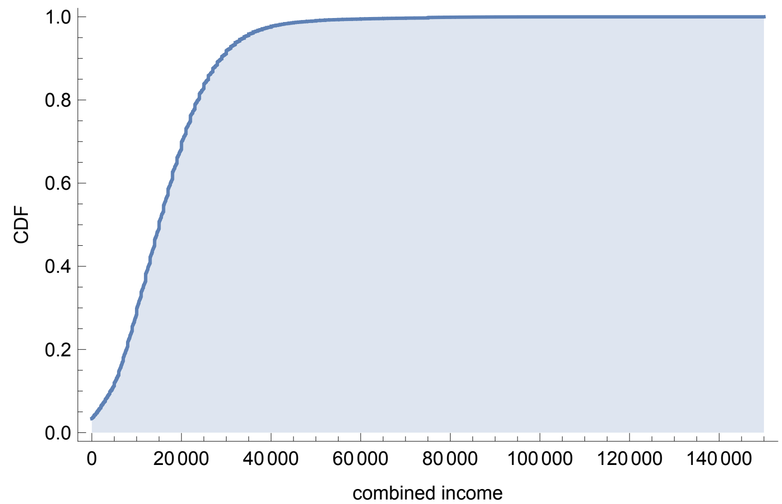
Figure 25: Lorenz curve for household income, 1980.



7 Counterfactual Experiments

In this section I discuss two counterfactual experiments and their effects on the distribution of matches, the level of assortative matching, and subsequently on inequality. Given that the level of assortative matching is an endogenous outcome of the marriage market, I

Figure 26: CDF for couple income, 1980.



cannot change it arbitrarily within the model, rather I shift it by changing its underlying determinants: the distribution of available singles in the marriage market, and preferences for partners educations. I explore both of those channels in the counterfactuals below.

7.1 Computation of Counterfactuals

Before proceeding further, here I briefly discuss the computation of the counterfactual experiments. Given a set of estimated parameters in the second stage $\widehat{\Pi}_{ij}$ and the distribution of available types m_i, f_j, equations 10 and 11 can be used to obtain the counterfactual distribution of marriages $\widehat{\mu}_{ij}$ and single individuals $\widehat{\mu}_{i0}$, $\widehat{\mu}_{0j}$. The counterfactual distribution of single individuals $\widehat{\mu}_{i0}$ and $\widehat{\mu}_{0j}$, which must satisfy the following equations:

$$m_i - \mu_{i0} = \sum_{j\in\Omega} \widehat{\Pi}_{ij} \sqrt{m_i f_j} \prod_{k=0}^{T(i,j)-1} \left(\frac{\mu_{i+k0}\mu_{0j+k}}{m_{i+k} f_{j+k}} \right)^{1/2(\beta(1-\delta))^k}, \tag{25}$$

$$f_j - \mu_{0j} = \sum_{i\in\Omega} \widehat{\Pi}_{ij} \sqrt{m_i f_j} \prod_{k=0}^{T(i,j)-1} \left(\frac{\mu_{i+k0}\mu_{0j+k}}{m_{i+k} f_{j+k}} \right)^{1/2(\beta(1-\delta))^k}. \tag{26}$$

Then, obtain the distribution of counterfactual marriages μ_{ij} from equation 9. The system of equations 25, 26 consists of $2|\Omega|$ equations that must be solved for μ_{i0}, μ_{0j}, $\forall\, i, j \in \Omega$. In this paper, the system consists of 1974 equations with 1974 unknowns. I solve this system of equations using the Trust-Region method combined with Gauss-Newton updating. The fact that the model in Choo (2015) is identified and that the equilibrium is unique (Chen, 2016) ensures that a solution exists for this system of equations.

7.2 CF 1: Changing the distribution of available singles

How does the distribution of education of singles affect marriage patterns, the level of assortative matching, and household income inequality? To answer this question I first change the distribution of available singles in the marriage market. Specifically, I hold constant (the estimated) preferences, and the distribution of income given characteristics as in 1980, and impose the distribution of singles from 1990. This increases the level of education of available singles. This exercise allows me to assess how much assortative matching, and household income inequality change when there are more educated singles available to marry.

Under this new counterfactual, 444,136 new marriages are formed (an increase of 15.70% from the number of observed marriages). Figures 27 and 29, and Tables 8 and 9 show the resulting pattern of marriages. There is a small but obvious shift to the right and down in the distribution of marriages by age of both men and women, as indicated in Figure 28. This means that both men and women delay the age at which they first marry, and also marry when they are older. Under CF1, men further delay marriage by 2.13 years on average, while women do by 1.90 years on average. Most interesting is the age at marriage of women under this counterfactual CF1. Under CF1, women aged from mid 20's to late 30's behave like men did in 1980, in terms of age at marriage. However, the correlation of ages of spouses in the resulting distribution of marriages is 0.81 (down from 0.82), and the correlation of education of spouses is 0.44 (down from 0.48). There are more heterogeneous marriages overall.

With respect to assortative matching on education, as we see in Figure 30, both men and women with higher education marry more often than before, and that people with lower education marry less often than before. And in fact, it is women with higher education the side of the market that marries more often, while men with lower education are then ones who marry less often.

In this counterfactual, the distribution of income is held constant at 1980 levels. Therefore, it is no surprise that the Gini coefficient for the counterfactual distribution of joint incomes is 0.327, very close to the Gini coefficient of the data. All this suggests that changes in the composition of available singles from 1980 to 1990 is not enough to explain the increase in inequality across married households over time. Indeed, when I impose the distribution of income prevalent in 1990, the Gini coefficient increases to 0.365, an increase of 11.62%. This is in line with other research suggesting that a combination of factors (mainly the increase in the skilled wage premium) is responsible for the increase in household income inequality over the last decades.

Figure 27: Pattern of marriages in CF1 by age of couple.

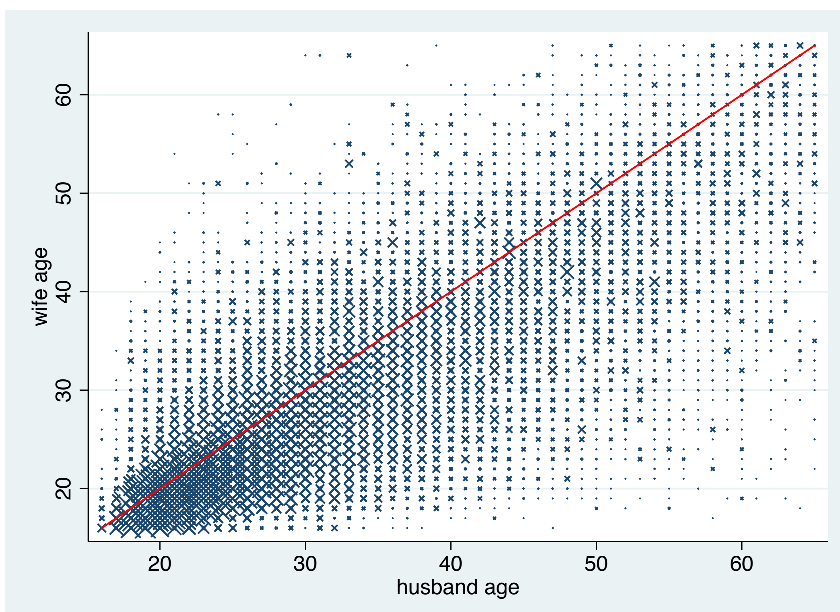


Table 8: Marriages by age of couple in CF1.

	husband age										
wife age	16-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-65	Total
16-19	20,359	43,881	8,671	2,089	501	121	15	13	9	13	75,672
	4.58	9.88	1.95	0.47	0.11	0.03	0.00	0.00	0.00	0.00	17.04
20-24	5,574	78,543	48,098	15,365	4,391	1,108	332	73	61	28	153,573
	1.26	17.68	10.83	3.46	0.99	0.25	0.07	0.02	0.01	0.01	34.58
25-29	611	14,888	39,637	24,946	10,290	3,406	1,034	273	87	27	95,199
	0.14	3.35	8.92	5.62	2.32	0.77	0.23	0.06	0.02	0.01	21.43
30-34	209	2,891	10,889	18,834	12,653	5,705	2,378	743	184	89	54,575
	0.05	0.65	2.45	4.24	2.85	1.28	0.54	0.17	0.04	0.02	12.29
35-39	45	617	2,347	5,391	9,598	7,001	2,887	1,509	447	179	30,021
	0.01	0.14	0.53	1.21	2.16	1.58	0.65	0.34	0.10	0.04	6.76
40-44	1	175	532	1,675	2,902	4,366	4,231	2,164	756	197	16,999
	0.00	0.04	0.12	0.38	0.65	0.98	0.95	0.49	0.17	0.04	3.83
45-49	0	22	125	290	733	1,816	2,689	2,198	1,027	690	9,590
	0.00	0.00	0.03	0.07	0.17	0.41	0.61	0.49	0.23	0.16	2.16
50-54	0	35	17	101	187	410	680	1,312	1,387	773	4,902
	0.00	0.01	0.00	0.02	0.04	0.09	0.15	0.30	0.31	0.17	1.10
55-59	0	2	7	23	91	81	175	400	706	739	2,224
	0.00	0.00	0.00	0.01	0.02	0.02	0.04	0.09	0.16	0.17	0.50
60-65	0	0	0	22	3	15	42	144	214	941	1,381
	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.05	0.21	0.31
Total	26,799	141,054	110,323	68,736	41,349	24,029	14,463	8,829	4,878	3,676	444,136
	6.03	31.76	24.84	15.48	9.31	5.41	3.26	1.99	1.10	0.83	100.00

Figure 28: Pattern of marriages in CF1 by age of couple.

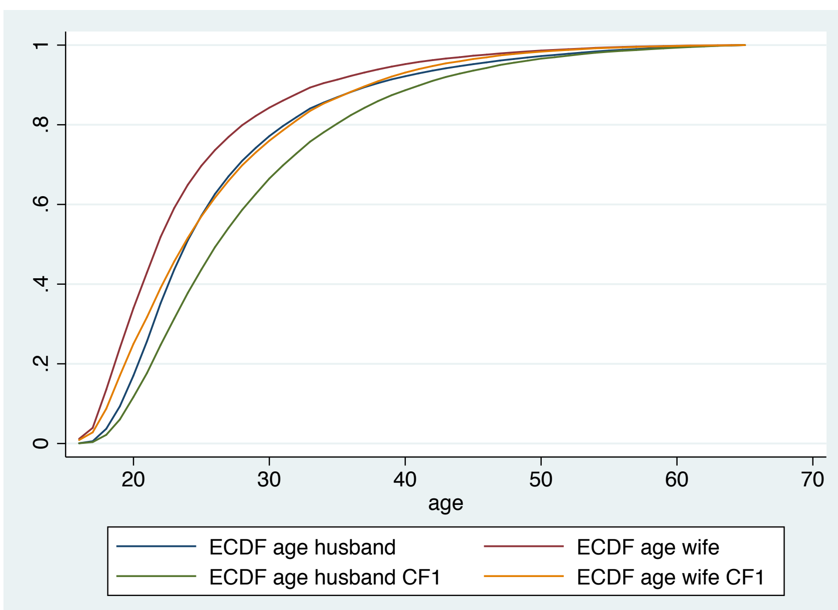


Figure 29: Pattern of marriages in CF1 by education of couple.

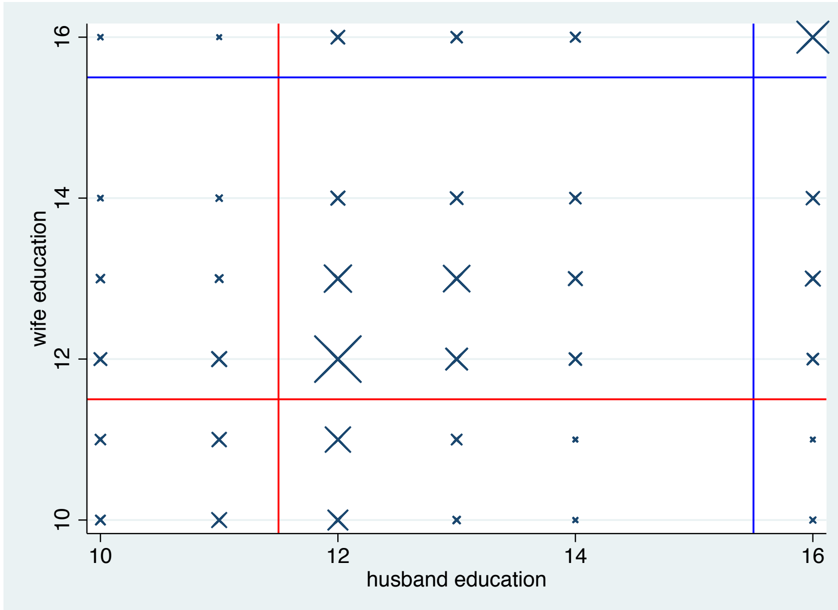
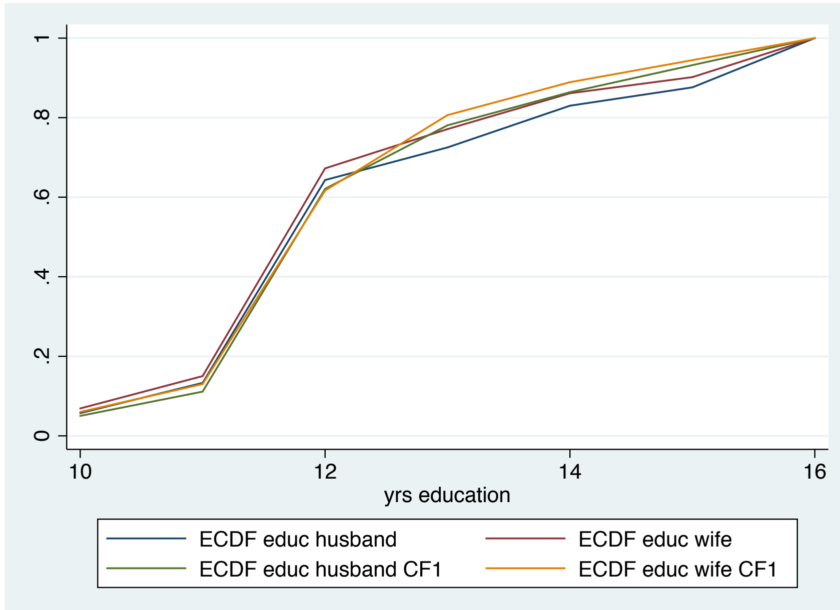


Table 9: Marriages in CF1 by education of couple.

wife education	husband education HS-	HS	C-	C	Total
HS-	16,978	32,109	7,536	1,206	57,829
	3.82	7.23	1.70	0.27	13.02
HS	24,544	132,944	43,013	15,586	216,087
	5.53	29.93	9.68	3.51	48.65
C-	6,922	49,417	45,892	18,738	120,969
	1.56	11.13	10.33	4.22	27.24
C	976	11,961	11,446	24,868	49,251
	0.22	2.69	2.58	5.60	11.09
Total	49,420	226,431	107,887	60,398	444,136
	11.13	50.98	24.29	13.60	100.00

Figure 30: Pattern of marriages in CF1 by education of couple.



7.3 CF 2: Changing matching on education

How much do preferences for partner's education affect marriage patterns, assortative matching, and household income inequality? For this second second counterfactual exercise, I shut down preferences for matching on education. I implement this by first regressing the gains from marriage on a polynomial function of age and years of education with race dummies.[22] After obtaining those regression estimates, I can compute the counterfactual gains from marriage when people do not care their partner's education and study its effect on household income inequality.

Here, there are 234,671 new marriages formed, a reduction of 38.86% from the baseline. There is virtually no change in age of marriage from the baseline, as indicated in Figure 32. However, there are large changes in marriages by education. At all levels of education, men

[22]Choo and Siow (2006) suggested this regression approach to conduct counterfactual exercises after estimating the gains from marriage. In addition to the regression, I scale up the utilities of marriage such that the mean estimated utility of marriage remains constant between the estimates and the utility after shutting down preferences for education. This last step is necessary to "compensate" individuals for a lower utility level after shutting down preferences for education.

and women marry more often than in the baseline. This is especially evident for people of lower education.

The correlation between education of spouses decreases to 0.11, while the correlation between age of spouses remains at 0.82. Figures 31, 33 show the resulting pattern of marriages. There is still some remaining correlation in the education levels of the spouses because age and education are correlated, especially at relatively younger ages, which is when most marriages occur. The calculated Gini coefficient is 0.334, using the distribution of incomes from 1980. When imposing the distribution of income from 1990, the Gini coefficient increases to 0.391. This suggests, again, that assortative matching along education plays a minor role in the increase of household income inequality over time.

Figure 31: Pattern of marriages in CF2 by age of couple.

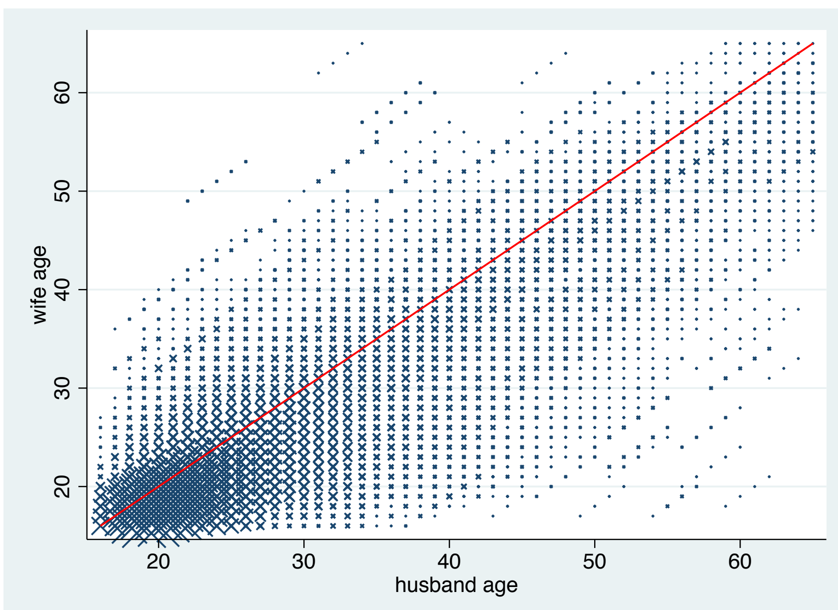


Table 10: Marriages by age of couple in CF2.

	husband age										
wife age	16-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-65	Total
16-19	17,338	34,704	5,933	1,310	271	77	7	5	10	2	59,657
	7.39	14.79	2.53	0.56	0.12	0.03	0.00	0.00	0.00	0.00	25.42
20-24	5,517	52,967	27,108	7,121	1,815	521	96	33	19	7	95,204
	2.35	22.57	11.55	3.03	0.77	0.22	0.04	0.01	0.01	0.00	40.57
25-29	536	7,739	16,747	9,353	3,433	1,157	274	113	27	3	39,382
	0.23	3.30	7.14	3.99	1.46	0.49	0.12	0.05	0.01	0.00	16.78
30-34	116	1,457	4,205	6,221	4,082	1,686	774	147	39	27	18,754
	0.05	0.62	1.79	2.65	1.74	0.72	0.33	0.06	0.02	0.01	7.99
35-39	21	251	807	1,781	2,926	2,299	1,083	531	93	24	9,816
	0.01	0.11	0.34	0.76	1.25	0.98	0.46	0.23	0.04	0.01	4.18
40-44	1	43	150	393	852	1,538	1,306	779	282	51	5,395
	0.00	0.02	0.06	0.17	0.36	0.66	0.56	0.33	0.12	0.02	2.30
45-49	0	3	33	79	176	444	970	839	394	117	3,055
	0.00	0.00	0.01	0.03	0.07	0.19	0.41	0.36	0.17	0.05	1.30
50-54	0	6	7	39	45	107	286	597	580	296	1,963
	0.00	0.00	0.00	0.02	0.02	0.05	0.12	0.25	0.25	0.13	0.84
55-59	0	0	0	4	35	20	71	161	382	403	1,076
	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.07	0.16	0.17	0.46
60-65	0	0	0	4	12	1	5	31	54	262	369
	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.02	0.11	0.16
Total	23,529	97,170	54,990	26,305	13,647	7,850	4,872	3,236	1,880	1,192	234,671
	10.03	41.41	23.43	11.21	5.82	3.35	2.08	1.38	0.80	0.51	100.00

Figure 32: Pattern of marriages in CF2 by age of couple.

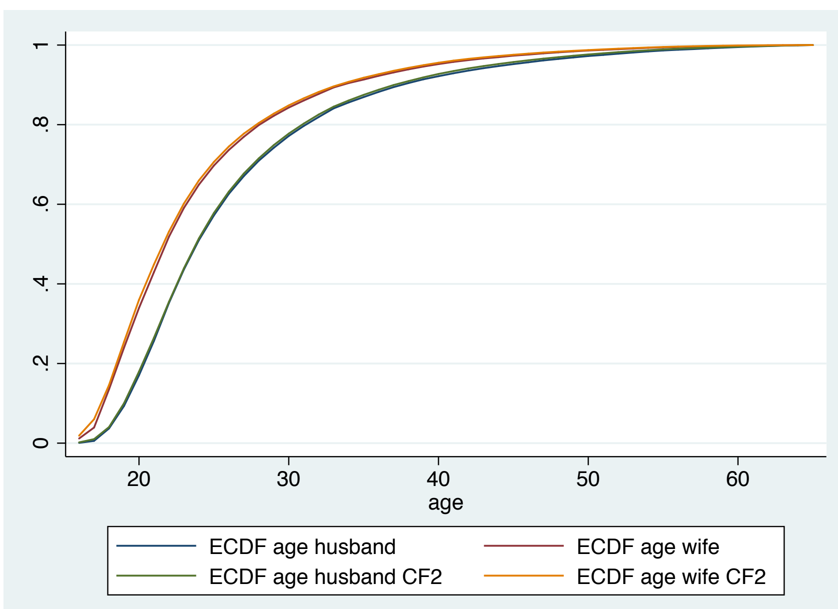


Figure 33: Pattern of marriages in CF2 by education of couple.

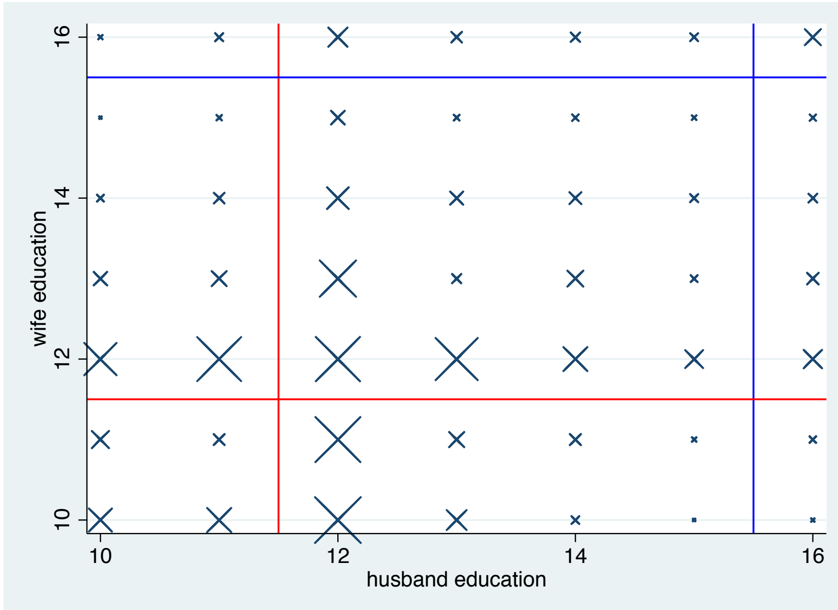
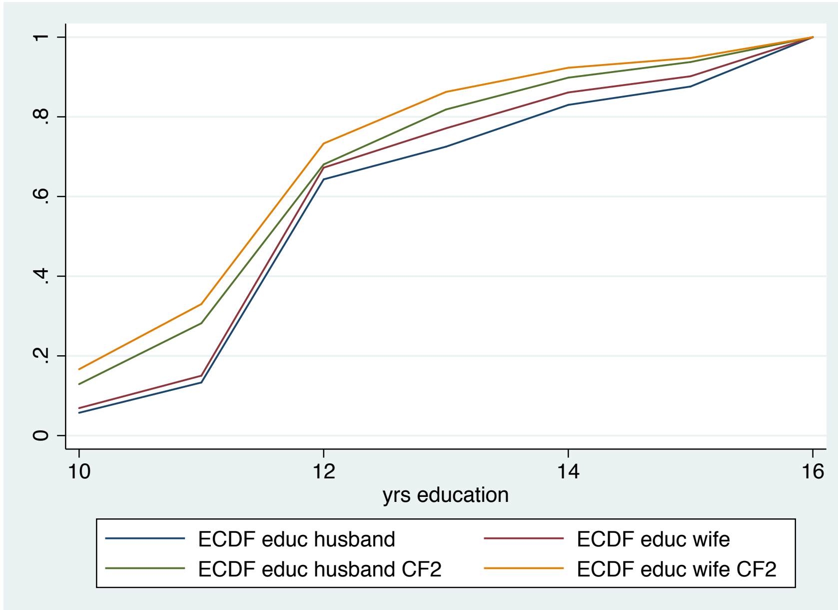


Table 11: Marriages in CF2 by education of couple.

wife education	husband education HS-	HS	C-	C	Total
HS-	18,818	41,245	14,856	2,537	77,456
	8.02	17.58	6.33	1.08	33.01
HS	33,416	21,255	32,699	7,228	94,598
	14.24	9.06	13.93	3.08	40.31
C-	12,014	25,180	9,855	3,285	50,334
	5.12	10.73	4.20	1.40	21.45
C	1,917	5,857	2,921	1,588	12,283
	0.82	2.50	1.24	0.68	5.23
Total	66,165	93,537	60,331	14,638	234,671
	28.19	39.86	25.71	6.24	100.00

Figure 34: Pattern of marriages in CF2 by education of couple.



8 Conclusion

In this paper, I study the the role of educational assortative matching in determining household income inequality. I develop and estimate a two-stage dynamic discrete choice model of educational attainment and marriage decisions. I document the existence of educational assortative matching along age and education. My results suggest that assortative matching along age is stronger than assortative matching along education. These results are driven mainly by large gains from marriage when the ages of the partners are close to each other.

I propose several counterfactual experiments designed to address how educational assortative matching affects income inequality. First, *ceteris paribus*, I combine the distribution of available singles from 1990 with the estimated gains from marriage from 1980. I find that the resulting distribution of marriages is virtually indistinguishable from the observed marriages in 1980. This results in a distribution of household incomes similar to that of 1980, which in turns results in similar level of inequality. However, imposing together the distribution of singles and the distribution of income in 1990, inequality rises 11.62%.

Second, I shut down matching along education levels on the estimated gains from marriage. I find that there is a large reduction in the number of marriages, along with a large reduction in the level of assortative marriages along education. The level of assortative marriages along age remains similar to the observed levels in 1980. However, when imposing incomes as in 1980, the Gini coefficient of inequality remains at similar levels to the observed data. With incomes as in 1990, the Gini coefficient increases to 0.388 (an increase of 16.87%). This suggests that preferences for partners of similar education, while explaining the sorting of partners along education levels, play a minor role in the resulting inequality of household income.

In contrast to previous findings,[23] the results of the counterfactual experiments suggest that the observed increase in household income inequality over time cannot be blamed on assortative matching alone. Assortative matching on education rather works as an amplifier of the underlying inequality across educational groups. These findings are complementary to work by Greenwood et al. (2016) which likewise find that assortative matching *in combination with other factors* amplifies household income inequality.

An interesting finding in my results is the fact that in the presence of a better educated population of singles (as in CF1 above using the distribution of singles from 1990), both men and women delay marriage. Age at marriage increases 2.13 years for men, and 1.90 for women compared to the baseline year. That is, keeping preferences constant the model can generate a delay in marriage with an increase in the educational attainment of singles and without relying on other external factors. I can attribute that to the change in the distribution of singles along education since age at marriage does not change when I shut down preferences for matching on education. This complements the introduction of the

[23] Some examples of work finding a positive association between inequality and positive assortative matching are Burtless (1999), Fernandez (2005), and Schwartz (2010).

contraceptive pill as an explanation for the observed rise in the age at marriage (Goldin and Katz, 2002; Bailey, 2006).

References

Arcidiacono, Peter and Robert A. Miller, "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, 2011, *79* (6), 1823–1867.

Atkinson, Anthony B. and Salvatore Morelli, "Chartbook of Economic Inequality," 2014.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, "Trends in U.S. Wage Inequality: Revising the Revisionists," *Review of Economics and Statistics*, May 2008, *90* (2), 300–323.

Bailey, Martha J., "More Power to the Pill: The Impact of Contraceptive Freedom on Women's Life Cycle Labor Supply," *Quarterly Journal of Economics*, 2006, *121* (1).

Beck, Audrey and Carlos González-Sancho, "Educational Assortative Mating and Children's School Readiness," 2009.

Becker, Gary S., "A Theory of Marriage: Part I," *Journal of Political Economy*, 1973, *81* (4), 813–846.

_ , "A Theory of Marriage: Part II," *Journal of Political Economy*, 1974, *82* (2).

Blossfeld, Hans-Peter, "Educational Assortative Marriage in Comparative Perspective," *Annual Review of Sociology*, 2009, *35* (1), 513–530.

Bound, John and Sarah Turner, "Dropouts and Diplomas: The Divergence in Collegiate Outcomes," in "Handbook of the Economics of Education Volume 4" 2011, chapter 8, pp. 573–613.

Breen, Richard and Leire Salazar, "Educational Assortative Mating and Earnings Inequality in the United States," *American Journal of Sociology*, 2011, *117* (3), 808–843.

Bruze, Gustaf, Michael Svarer, and Yoram Weiss, "The Dynamics of Marriage and Divorce," *Journal of Labor Economics*, January 2015, *33* (1), 123–170.

Burtless, Gary, "Effects of growing wage disparities and changing family composition on the U.S. income distribution," *European Economic Review*, 1999, *43.*

Cancian, Maria and Deborah Reed, "The impact of wives' earnings on income inequality: issues and estimates.," *Demography*, May 1999, *36* (2), 173–84.

Chen, Liang, "Identification and Estimation of Empirical Dynamic Matching Models," 2016.

Chiappori, Pierre-Andre, *Matching with Transfers: The Economics of Love and Marriage*, Princeton University Press, 2017.

Chiappori, Pierre-André, Bernard Salanié, and Yoram Weiss, "Partner Choice, Investment in Children, and the Marital College Premium," *American Economic Review*, 2017, *107* (8), 2109–2167.

Chiappori, Pierre-Andre, Monica Costa Dias, and Costas Meghir, "The Marriage Market, Labor Supply and Education Choice," 2015.

_ , Murat Iyigun, and Yoram Weiss, "Investment in schooling and the marriage market," *The American Economic Review*, 2009, *99* (5), 1689–1713.

Choo, Eugene, "Dynamic Marriage Matching: An Empirical Framework," *Econometrica*, 2015, *83* (4), 1373–1423.

_ and Aloysius Siow, "Who marries whom and why," *Journal of Political Economy*, 2006, *114* (1), 175–201.

Deere, Donald R. and Jelena Vesovic, "Educational Wage Premiums and the U.S. Income Distribution: A Survey," in "Handbook of the Economics of Education, Volume 1" 2006, chapter 6, pp. 255–306.

Eckstein, Zvi and Osnat Lifshitz, "Dynamic Female Labor Supply," *Econometrica*, 2011, *79* (6), 1675–1726.

_ , Michael Keane, and Osnat Lifshitz, "Career and Family Decisions: Cohorts born 1935-1975," *Econometrica*, 2019.

Eika, Lasse, Magne Mogstad, and Basit Zafar, "Educational Assortative Mating and Household Income Inequality," *Journal of Political Economy*, 2018, *forthcoming.*

Fernandez, Raquel, "Love and Money: A Theoretical and Empirical Analysis of Household Sorting and Inequality," *The Quarterly Journal of Economics*, 2005, *120* (1), 273–344.

_ and Richard Rogerson, "Sorting and Long-Run Inequality," *The Quarterly Journal of Economics*, 2001, *116* (4), 1305–1341.

Goldin, Claudia and Lawrence F. Katz, "The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions," *Journal of Political Economy*, 2002, *110* (4), 730–770.

Greenwood, Jeremy, Nezih Guner, Georgi Kocharkov, and Cezar Santos, "Marry Your Like: Assortative Mating and Income Inequality," *The American Economic Review Papers and Proceedings*, 2014, *104* (5), 3–5.

_ , _ , _ , and _ , "Technology and the changing family: a unified model of marriage, divorce, educational attainment and married female labor-force participation," *American Economic Journal: Macroeconomics*, 2016, *8* (1).

Hotz, V. Joseph and Robert A. Miller, "Conditional Choice Probabilities and the Estimation of Dynamic Models," *The Review of Economic Studies*, 1993, *60* (3), 497–529.

Hryshko, Dmytro, Chinhui Juhn, and Kristin McCue, "Trends in Earnings Inequality and Earnings Instability among U.S. Couples: How Important Is Assortative Matching?," 2014.

Isen, Adam and Betsey Stevenson, "Women's Education and Family Behavior: Trends in Marriage, Divorce and Fertility," 2010.

Katz, Lawrence F. and David H. Autor, "Changes in the Wage Structure and Earnings Inequality," in "Handbook of Labor Economics, Volume 3A" 1999.

Keane, Michael P. and Kenneth I. Wolpin, "The Role of Labor and Marriage Markets, Preference Heterogeneity, and the Welfare System in the Life Cycle Decisions of Black, Hispanic, and White Women," *International Economic Review*, 2010, *51* (3), 851–892.

Kremer, Michael, "How Much Does Sorting Increase Inequality?," *The Quarterly Journal of Economics*, 1997, *112* (1), 115–139.

Liu, Haoming and Jingfeng Lu, "Measuring the degree of assortative mating," *Economics Letters*, 2006, *92* (3), 317–322.

Low, Corinne, "Pricing the Biological Clock: Reproductive Capital on the US Marriage Market," 2016.

Neal, Derek, "Why Has Black-White Skill Convergence Stopped?," in "Handbook of the Economics of Education, Volume 1" 2006, chapter 9, pp. 511–576.

Rust, John, "Structural Estimation of Markov Decision Processes," in "Handbook of Econometrics," Vol. 1 1994.

Schwartz, Christine R., "Earnings Inequality and the Changing Association between Spouses' Earnings," *American Journal of Sociology*, March 2010, *115* (5), 1524–1557.

_ , "Trends and Variation in Assortative Mating: Causes and Consequences," *Annual Review of Sociology*, July 2013, *39* (1), 451–470.

_ **and Robert D. Mare**, "Trends in Educational Assortative Marriage from 1940 to 2003," *Demography*, 2005, *42* (4), 621–646.

Stevenson, Betsey and Justin Wolfers, "Marriage and Divorce: Changes and their Driving Forces," *Journal of Economic Perspectives*, May 2007, *21* (2), 27–52.

Yitzhaki, Shlomo and Edna Schechtman, "More Than a Dozen Alternative Ways of Spelling Gini," in "The Gini Methodology: A Primer on a Statistical Methodology," Springer, 2013, chapter 2, pp. 2–xvi, 548.