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ABSTRACT

We investigate the pattern of educational assortative mating, its evolution over time, and its impact on household income inequality. To these ends, we use rich data from the U.S. and Norway over the period 1980-2007. We find evidence of positive assortative mating at all levels of education in both countries. However, the time trends vary by the level of education: Among college graduates, assortative mating has been declining over time, whereas low educated are increasingly sorting into internally homogenous marriages. When looking within the group of college educated, we find strong but declining assortative mating by academic major. These findings motivate and guide a decomposition analysis, where we quantify the contribution of various factors to the distribution of household income. We find that educational assortative mating accounts for a non-negligible part of the cross-sectional inequality in household income. However, changes in assortative mating over time barely move the time trends in household income inequality. This is because the decline in assortative mating among the highly educated is offset by an increase in assortative mating among the low educated. By comparison, increases in the returns to education over time generate a considerable rise in household income inequality, but these price effects are partly mitigated by increases in college attendance and completion rates among women.

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1. Introduction

It is often argued that individuals are increasingly sorting into internally homogenous marriages, and that this assortative mating has led to a rise in household income inequality. This widespread view is supported by two empirical facts. The proportion of couples who share the same level of schooling has been growing over the past few decades (see e.g. Pencavel, 1998; Schwartz and Mare, 2005). Accompanying this increase in educational homogamy, there has been a rise in household income inequality (see e.g. Western, Bloome and Percheski, 2008). In the U.S., for example, the probability that a college graduate is married to someone with a college degree increased by 120 percent between 1980 and 2007, while the Gini coefficient in household income among married couples increased from 33.1 to 40.3 over this period.

In this paper, we investigate the pattern of educational assortative mating, its evolution over time, and its impact on household income inequality. This has proven difficult for several reasons. One challenge is to distinguish between secular changes in educational attainment of men and women and shifts in educational assortative mating.[1] For example, the closing of the gender gap in higher education may increase the probability that a college graduate is married to someone with a college degree, even if there were no changes in the assortativeness of marriage (see e.g. Liu and Lu, 2006). Another challenge is that the economic returns to education have increased considerably over the past few decades.[2] As a result, educational assortative mating may become increasingly important for the distribution of household income, even if there were no changes in the mating pattern.

This paper addresses these challenges and makes two key contributions. We begin by examining the degree of educational assortative mating, how it evolves over time, and the extent to which it differs between countries. The size and detailed nature of the data we are using allows us to bring new evidence

[1] See Goldin and Katz (2009) for a detailed description of the evolution in educational attainment of men and women in the U.S.

[2] See e.g. Autor, Katz, and Kearney (2008). Following much of this literature, we will refer to the coefficients on education levels in regressions of income on educational attainment and potential experience as ‘returns to education’. As shown in Heckman, Lochner and Todd (2006), these regressions do not identify internal rates of return to investment in education, and the estimated coefficients should rather be interpreted as representing income differentials by education levels.

on the assortativeness of marriage over time and between countries. This evidence motivates and guides a decomposition analysis, quantifying the contribution of various factors to household income inequality. We apply the semiparametric decomposition method proposed by DiNardo, Fortin, and Lemieux (1996) to address questions such as: What is the relative importance of changes in educational composition, returns to education, and educational assortative mating for the rise in household income inequality? Which of these factors are important for the differences in household income inequality between countries?

Our analysis uses rich micro data from the U.S. and Norway over the period 1980-2007. These countries have different levels but comparable trends in household income inequality. Since 1980, the returns to education have increased considerably in both countries. At the same time, they experienced an increase in homogamy among the highly educated, while college attendance and completion rates of women caught up with that of men. By comparing the results across the two countries, we shed light on whether our findings are common to economies that differ in the incentives to sort into internally homogenous marriages, due to differences in coverage and generosity of social programs as well as in wage-setting institutions (such as unions and minimum wage standards).

To avoid confounding educational assortative mating with changes in the educational composition of men and women, we measure marital sorting between education levels i and j as the observed probability that a woman with education level i is married to a man with education level j, relative to the probability under random matching with respect to education. Positive (negative) assortative mating means that men and women with the same level of education marry more (less) frequently than what would be expected under a marriage pattern that is random in terms of education. In the empirical analysis, we refine this approach to account for sorting by age and changes in the probability of marriage by education level.

During the entire sample period, there is evidence of positive assortative mating at all levels of education in both the U.S. and Norway. However, the time trends are heterogeneous and vary depending on where in the educational distribution one looks. On the one hand, assortative mating has declined in both countries among the highly educated. In 1980, Americans with a college degree were three times as likely to be married to a spouse with a college degree, compared to the counterfactual situation where spouses were randomly matched with respect to education; in 2007, they were only twice as likely. On the other hand, assortative mating has increased among the low educated, especially in the U.S. In 1980, Americans without a high school degree were three times as likely to be married to one another as compared to the probability with random mating; in 2007, they were six times as likely.

Exploiting the exceptionally rich Norwegian data, we further demonstrate that assortative mating is even stronger by college major than by education level. The assortativeness is strongest for medicine and law, which have the highest economic returns. In 1980, for example, a law graduate was 75 times as likely to be married to another graduate with a law degree, compared to the counterfactual situation where spouses were randomly matched. By comparison, college graduates as a whole were only 4.4 times as likely to be married to one another as compared to the probability with random mating. The assortative mating by college major declines over time but remains sizable. In 2007, law graduates were still 29 times as likely to be married to one another, relative to the probability under random matching with respect to education.

After documenting the patterns of educational assortative mating, we apply the decomposition method to quantify the contribution of various factors to household income inequality. Our findings may be summarized with four broad conclusions. First, educational assortative mating accounts for a non-negligible part of the cross-sectional inequality in household income. For example, our results suggest the Gini coefficient in 2007 is 5% (4%) higher in the U.S. (Norway) compared to the counterfactual situation where spouses were randomly matched. Second, the changes in assortative mating over time barely moved the time trends in household income inequality. This is because the decline in assortative mating among the highly educated was offset by an increase in assortative mating among the low educated. Third, increases in the returns to education generated a considerable rise in household income inequality, but these price effects were partly mitigated by increases in college attendance and completion rates among women. In the U.S., for example, our estimates suggest the Gini coefficient in 2007 would have been 23% lower if returns to education had remained at their 1980 levels. By way of comparison, the Gini coefficient would have been 6% higher had the educational composition in 2007 been like that in 1980. Fourth, the relatively high levels of inequality in the U.S. as compared to Norway cannot be explained by differences in assortative mating. By contrast, the high returns to education in the U.S. accounts for much of the cross-country difference in inequality.

In interpreting these findings, it is important to keep in mind the descriptive nature of our analysis. While our study carefully describes educational assortative mating over time and across countries, it is silent on the underlying forces of the mating patterns.[3] The decomposition method is also best understood as a descriptive approach, where observed outcomes for one group are used to construct counterfactual scenarios for another group. In constructing these scenarios, we follow the literature on decomposition methods in abstracting from potentially important partial equilibrium considerations (e.g. self-selection into education by comparative advantage) and general equilibrium conditions (e.g. simultaneous determination of education distributions and returns).[4] As a result, we are reluctant to give the decomposition a strict causal interpretation, but rather think of it as providing a first order approximation of the contribution of different factors to inequality.[5] Interpreted in this way, a key insight from our analysis is that changes in assortative mating have played a minor role to the rise in household income inequality.

Our study complements the prior empirical literature on educational assortative mating. One strand of this literature measures educational assortative mating as the correlation coefficient between couples' education levels (see e.g. Kremer, 1997; Pencavel, 1998; Fernández, Guner and Knowles, 2005). Another strand of the literature measures assortative mating as the proportion of couples who share the same level of schooling (see e.g. Mare, 1991; Pencavel, 1998; Fernández and Rogerson, 2001; Breen and Salazar,

[3] The analysis of Bertrand (2013) illustrates the difficulty of accurately measuring the costs and benefits of having a career or being married across groups of college-educated women. See also Chiappori, Iyigun and Weiss (2009) who present a model in which schooling generates a labor market return and a marriage-market return.

[4] See Fortin, Lemieux and Firpo (2011) for a review of decomposition methods in economics and a discussion of these considerations.

[5] For example, the return to education results may in part be driven by changes in labor supply over time (see e.g. Bertrand, Kamenica and Pan, 2013). While female labor supply has been increasing modestly over this time period, there is some evidence of college educated women opting out or reducing their labor supply after they marry or have children (see e.g. Bertrand, Goldin and Katz, 2010; Cha, 2010).

2011). A limitation of these measures is that the conclusions about assortative mating could be confounded by changes in the distribution of men's and women's education.[6] We address this issue and find that educational homogamy has increased because of changes in the educational composition of men and women, while changes in assortative mating have played a minor role. Our findings are broadly consistent with recent independent work by Greenwood et al. (2014), who show that the number of matches between husband and wife with identical education levels is larger than what would occur if matching were random.

Motivated by the substantial differences in labor market outcomes across post-secondary fields of study (Altonji, Blom and Meghir, 2012), we also provide some of the first evidence on assortative mating within the group of college educated. Our findings suggest the choice of college major is an important but neglected pathway through which individuals sort into internally homogenous marriages. However, accounting for assortative mating by college major does not materially affect the conclusions about the evolution of household income inequality; changes in educational composition and returns to education remain the key factors.

Our paper also contributes to a large and growing literature that aims at explaining the rise in economic inequality observed in many developed countries since the early 1980s. Most of the evidence is on the factors behind the increase in earnings inequality among males.[7] A smaller body of work has examined the trends in household income inequality. Some studies decompose the inequality in household income by income sources and subgroups (see e.g. Karoly and Burtless, 1995; Cancian and Reed, 1998; Aslaksen, Wennemo and Aaberge, 2005; Western, Bloome and Percheski, 2008; Breen and Salazar, 2011). Other studies use shift-share approaches to examine the change in income inequality accounted for by changes in male and female labor earnings distributions and changing household characteristics (see e.g. Burtless, 1999; Daly and Valletta, 2006; Larrimore, 2013; Greenwood et al., 2014). Our study complements this body of work by quantifying the relative importance of changes in

[6] See Liu and Lu (2006) for evidence on the biases in measures of assortative mating that do not control for changes in education distributions.
[7] See e.g. the reviews in Autor, Katz, and Kearney (2008) and Acemoglu and Autor (2010).

educational composition, returns to education, and educational assortative mating to household income inequality over time and between countries.

The remainder of this paper proceeds as follows. Section 2 describes our data and reports descriptive statistics. Section 3 presents our findings on educational assortative mating in the U.S. and Norway. Section 4 outlines the decomposition method and explores factors behind the evolution of household income inequality. The final section offers some concluding remarks.

2. Data and Descriptive Statistics

U.S. data. Our analysis employs the public use March Current Population Survey (CPS). We use the data sets for the period 1980-2007. In every year, the survey covers a nationally representative sample of households. The variables captured in the survey include individual demographic information (such as gender, date of birth, and marital status) and socioeconomic data (including educational attainment and income). The data contains unique family identifiers that allow us to match spouses. Our measure of individual income consists of wages and income from self-employment. In each year, we exclude individuals with missing information on income, and set negative income to zero. We measure household income by pooling the individual income of the spouses.

In the public use data, top codes are imposed on every source of income above a specific value. Since these thresholds change over time, the top coding may affect time trends in income inequality. To address this issue, we use the cell means series for top-coded incomes constructed by Larrimore et al. (2008): They show that the cell-mean adjusted public use March CPS does a better job of matching income inequality trends found in the internal March CPS than those previously available in the literature.

Norwegian data. Our analysis employs several registry databases maintained by Statistics Norway that we can link through unique identifiers for each individual. This allows us to construct a rich longitudinal data set containing records for every Norwegian from 1980 to 2007. The variables captured in this data set include individual demographic information (such as gender, date of birth, and marital status) and socioeconomic data (including educational attainment, market income). The data contains unique family identifiers that allow us to link spouses. To enhance comparability with the U.S. data, we construct a measure of individual income which consists of wages and income from self-employment. Additionally, in each year we exclude individuals with missing information on income, and set negative income to zero. Household income is measured by pooling the individual income of the spouses.

The coverage and reliability of Norwegian registry data are considered to be exceptional (Atkinson, Rainwater and Smeeding, 1995). Educational attainment is reported by the educational establishment directly to Statistics Norway, thereby minimizing any measurement error due to misreporting. We have information not only about years of schooling and highest completed degree, but also field of study or academic major in post-secondary education (including all universities and colleges). The Norwegian income data also has several advantages over those available in many other countries. First, there is no attrition from the original sample because of the need to ask permission from individuals to access their tax records. In Norway, these records are in the public domain. Second, our income data pertain to all individuals, and not only to jobs covered by social security as in several other registry data sets. Third, there are no reporting or recollection errors; the data come from individual tax records with detailed information about the different sources of income. To improve comparability with the U.S. data, we top code the Norwegian income data at the 99th percentile level. Throughout the paper, all monetary figures are reported in USD at 2007 levels, converted by exchange rates and adjusted for inflation.

Sample selection. We study the distribution of household income among married couples during the period 1980-2007. In each year, we consider couples where the mean of the husband’s and wife’s age is between 26 and 60 years. In the specification checks, we also show that the conclusions from the decomposition analysis are robust to accounting for changes in the probability of marriage by education levels.

In our main analysis, individuals are assigned to one of four mutually exclusive groups according to the highest level of education completed: no high school degree (< 12 years of schooling); high school graduates (12 years of schooling); individuals with some college (13-15 years of schooling); college graduates (> 15 years of schooling).[8] In Table 1, we document key characteristics of the samples of husbands and wives in each country. As expected, female labor force participation has grown over time. As a result, the incomes of females have increased, both in absolute levels and as shares of household income. At the same time, we can see a convergence in educational attainment of men and women.

Table 1: Summary Statistics

	U.S.				Norway			
	1980		2007		1980		2007	
	Wives	Husbands	Wives	Husbands	Wives	Husbands	Wives	Husbands
Sample means:								
Age	40.1	42.9	42.8	45.0	40.7	43.6	44.8	47.4
Years of education	12.3	12.6	13.7	13.7	9.7	10.5	12.4	12.5
Income ($ - 2007)	13275	50605	27739	59627	9440	29177	28502	48168
Labor force part.	0.633	0.931	0.742	0.914	0.744	0.970	0.924	0.959
Number of obs.	28565		32127		655032		520107	

Notes: This table reports average characteristics of husbands and wives in the U.S. and Norway. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. Labor force participation is defined as having positive labor income from wages or self-employment.

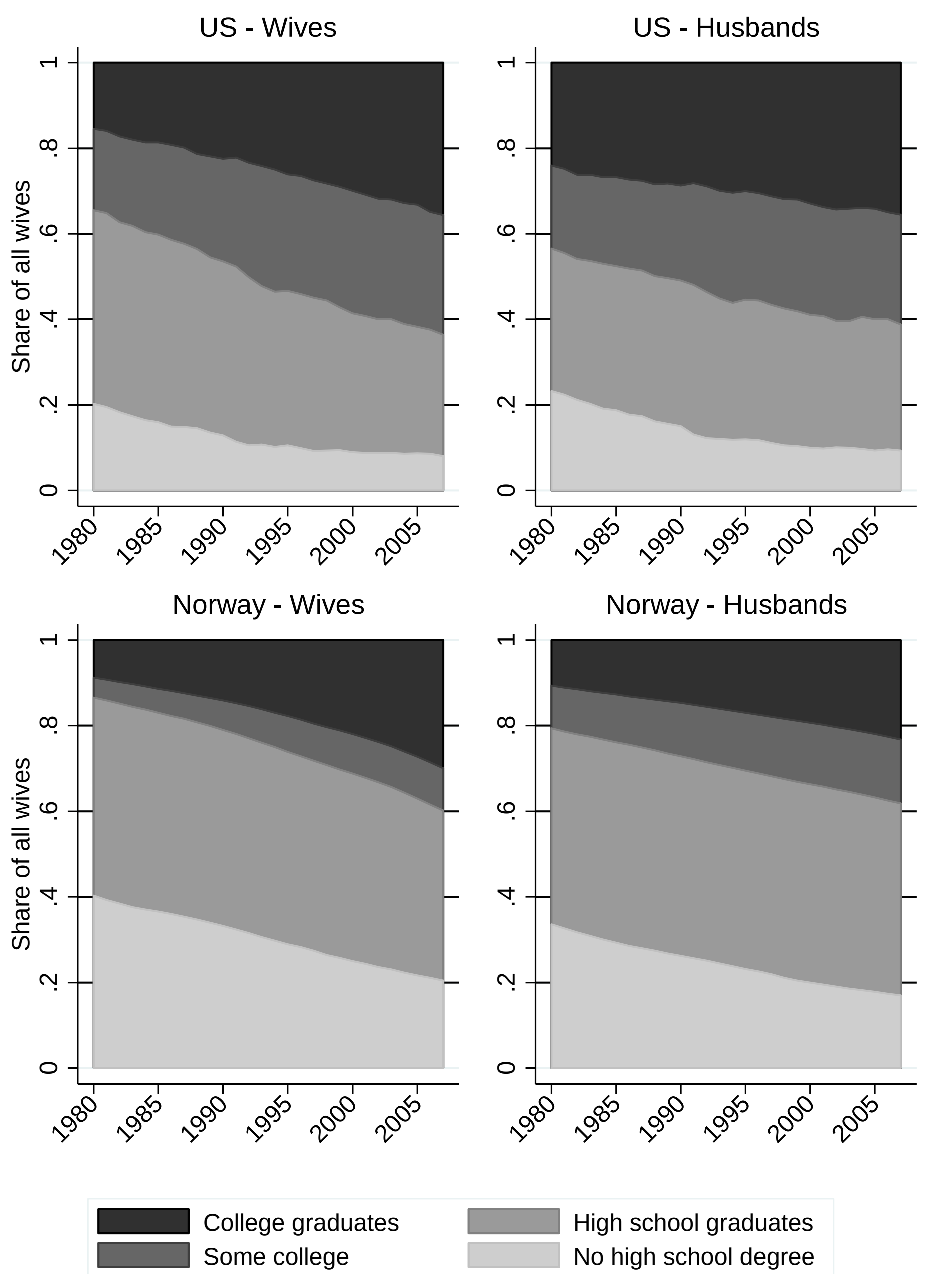
Descriptive statistics. Before turning to the examination of educational assortative mating, we describe a few important features of our data.

We begin by displaying the education distribution of husbands and wives over the period 1980-2007. The graphs in the upper part of Figure 1 show the time trends in the U.S. We can see that the proportion of husbands with a college degree starts out at around 24 percent in 1980 and increases to about 36 percent in 2007. By comparison, only 15 percent of the wives had a college degree in 1980. Over time, however, the educational attainment of women caught up with that of men, and the wives in 2007 are just as likely to have a college degree as the husbands. The graphs in the lower part of Figure 1 demonstrate that the time trends are quite similar in Norway: The proportion of husbands with bachelor or post-

[8] To enhance comparability between the education systems in the U.S. and Norway, we make two adjustments to the definition of education levels based on years of schooling. In Norway, certain types of high school degrees require only 10 or 11 years of schooling; we count individuals with these degrees as high school graduates. Several bachelor degrees in Norway only take three years of post-secondary study; we record all individuals with a three year or more post-secondary credential as college graduates.

graduate degree increased from 11 percent in 1980 to 23 percent in 2007, while the corresponding change for wives was from 9 to 30 percent. In both countries, the increases in college education were accompanied by substantial declines in the proportion of the population without a high school diploma.

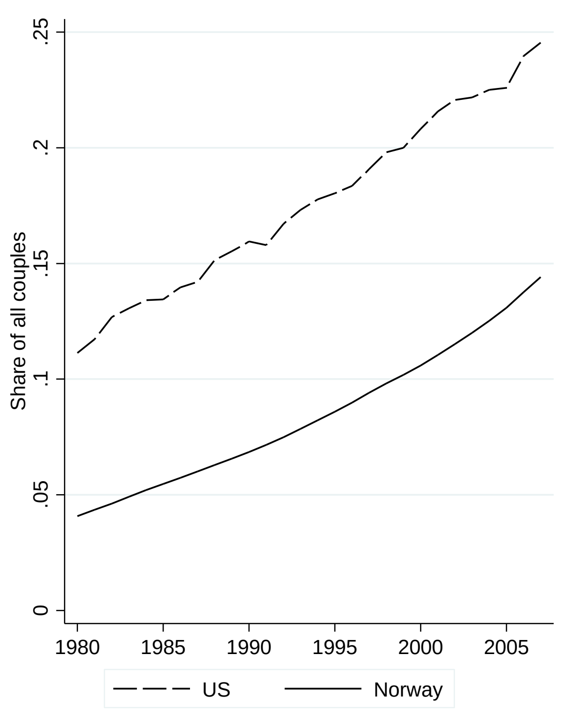
Figure 1: Time Trends in Husbands' and Wives' Educational Attainment



Notes: This figure displays the educational composition of wives and husbands over time in Norway and the U.S. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

Figure 2 shows how the closing of the gender gap in higher education is accompanied by an increase in homogamy among the college educated. In the U.S., for example, the probability of a college graduate marrying someone with a college degree increased by 13 percentage points between 1980 and 2007. A similar pattern is observed for Norway, where the proportion of couples in which both spouses are college educated increased from 4 percent to 14 percent over this period.

Figure 2: Proportion of Couples in which Both Spouses are College Educated



Notes: This figure displays the educational composition of wives and husbands over time in Norway and the U.S. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

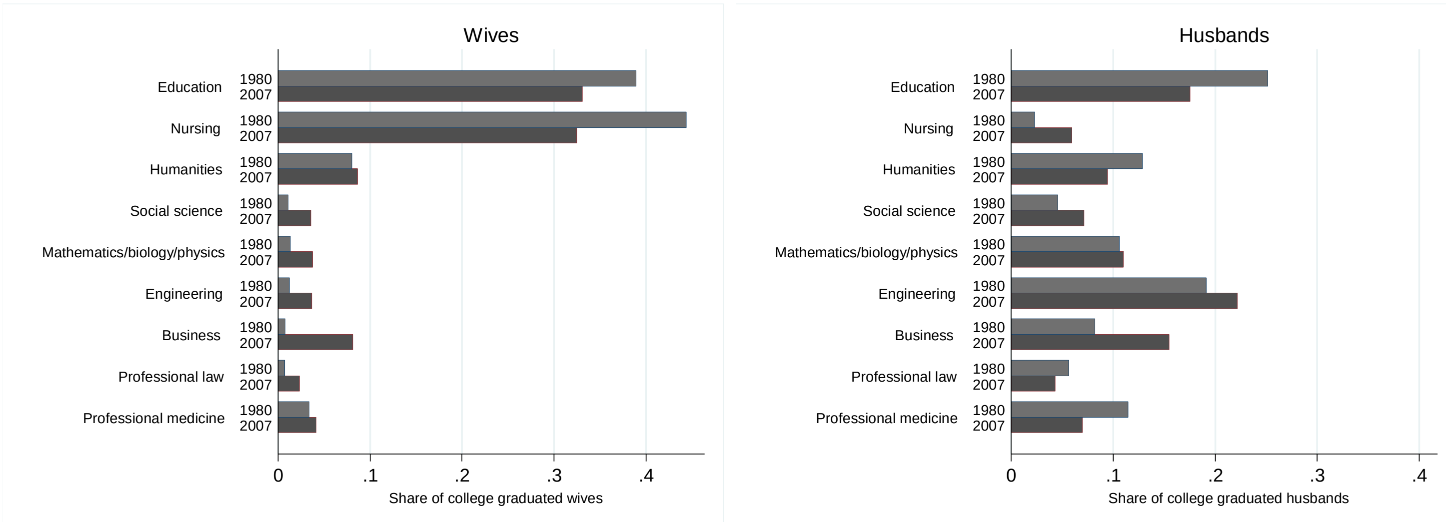
Alongside these changes in the education composition of husbands, wives, and couples, a large body of evidence suggests a rise in the labor market returns to education (see e.g. Autor, Katz, and Kearney, 2008; Acemoglu and Autor. 2010). Appendix Table A.1 confirms this pattern in our data, reporting income differentials of husbands and wives from OLS regressions of annual income on education levels (conditional on potential experience). In both countries, there are sizeable income premiums for high school and college degrees. The positive association between income and education is increasing from 1980 to 2007. In both years, the income differentials by education levels are most pronounced in the U.S.

In Figure 3, we take advantage of the detailed nature of the Norwegian data to examine the composition of college majors of husbands, wives, and couples. This figure displays the distribution of majors among the college educated in 1980 and 2007. The fields of study of both husbands and wives have changed substantially. In particular, college-educated women are much less likely to have nursing or education degrees in 2007 as compared to 1980. At the same time, there have been shifts towards more college-educated women graduating with degrees in high earning fields such as business, engineering, law and medicine. The trend for college-educated husbands is quite similar. The share with a degree in education has declined substantially, while the share with a business degree has increased. The most pronounced changes in educational homogamy by college major come from an increase in the fraction of couples with business degrees and a decline in the likelihood that both spouses have education degrees. In the aggregate, however, there is little change in educational homogamy by college major.

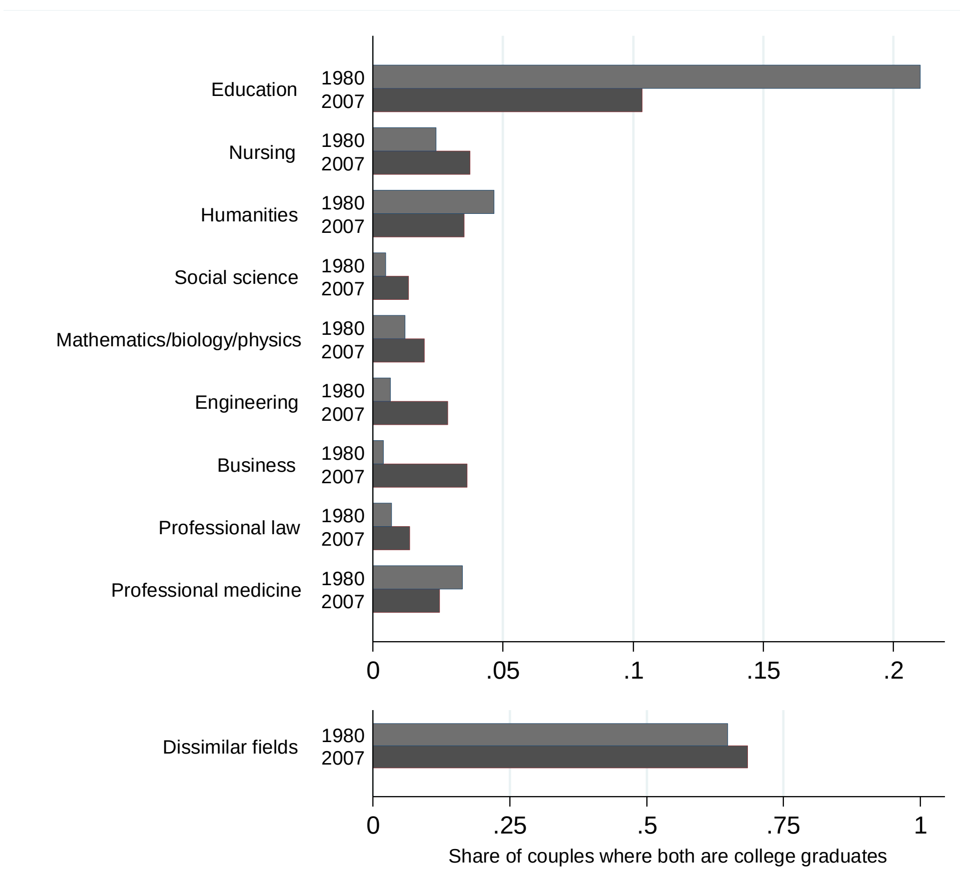
Appendix Table A.2 shows gender-specific income differentials by college major in 1980 and 2007 for Norway. In each year, we report OLS estimates of annual income on education levels and college major (conditional on potential experience) by gender. In line with previous evidence (see e.g. Altonji, Blom and Meghir, 2012), medicine, law, engineering, science and business command high income premiums, whereas individuals with humanities, nursing and education degrees tend to have relatively low income. These income differentials have become more pronounced over time.

Figure 3: College Educated by Majors in Norway, 1980 and 2007

Panel A: Distribution of Majors for Wives and Husbands



Panel B: Joint Distribution of College Majors



Notes: This figure displays the major composition among college educated wives, husbands, and couples. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

3. Educational Assortative Mating

Measure of educational assortative mating. We measure marital sorting between education levels *i* and *j* as the observed probability that a husband with education level *j* is married to a wife with education level *i*, relative to the probability under random matching with respect to education:

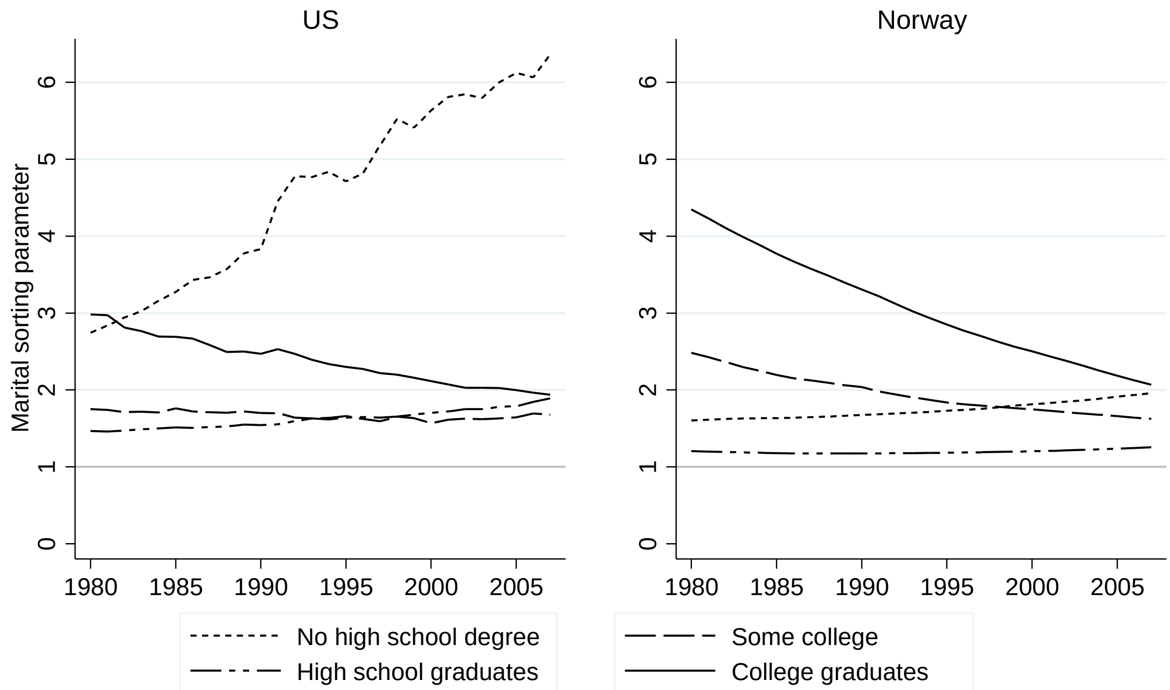
$$s_{ij} = \frac{\Pr\ (Wife = i \cap Husband = j)}{\Pr\ (Wife = i) \cdot \Pr\ (Husband = j)}. \tag{1}$$

Positive (negative) assortative mating means that men and women with the same level of education marry more (less) frequently than what would be expected under a marriage pattern that is random in terms of education: that is, the marital sorting parameter s_{ij} is larger (smaller) than one when *i* is equal to *j*.

In each year, we estimate the sorting parameters for every combination of education of the husbands and wives. The joint education distribution of the spouses is fully described by the marital sorting parameters and the marginal education distributions of wives and husbands. In a robustness analysis, we refine this approach to account for sorting by age and changes in the probability of marrying at all according to education level.

Assortative mating by level of education. Appendix Table A.3 reports the marital sorting parameters for all combinations of education levels in both the U.S. and Norway in 1980 and 2007. Figure 4 complements by displaying the sorting parameters on the diagonal, where husbands and wives have the same education level. During the entire sample period, there is evidence of positive assortative mating at all levels of education in both countries. The time trends, however, are heterogeneous and vary depending on where in the educational distribution one looks. We can see that assortative mating has declined among the highly educated. In 1980, Americans with a college degree were three times as likely to be married to a spouse with a college degree, compared to the counterfactual situation where spouses were randomly matched with respect to education; in 2007, they were only twice as likely. Conversely, assortative mating has increased among the low educated, especially in the U.S. In 1980, Americans without a high school degree were three times as likely to be married to one another as compared to the probability with random mating; in 2007, they were six times as likely.

Figure 4: Trends in Marital Sorting by Education Level



Notes: This figure displays the time trends in marital sorting parameters for which husbands and wives have the same education level. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

In the aggregate, however, the degree of assortative mating has changed little over the past few decades. Table 2 illustrates this by showing the weighted average of the marital sorting parameters along the diagonal. In both 1980 and 2007, Americans with the same level of education were about twice as likely to be married to one another as compared to the probability with random mating. By way of comparison, Norwegians in 1980 and 2007 were about 1.5 times as likely to be married to someone with the same level of education as compared to the probability with random mating. Taken together, these results suggest the observed increase in educational homogamy is in both countries driven by shifts in the education distribution of men and women, rather than stronger assortative mating.

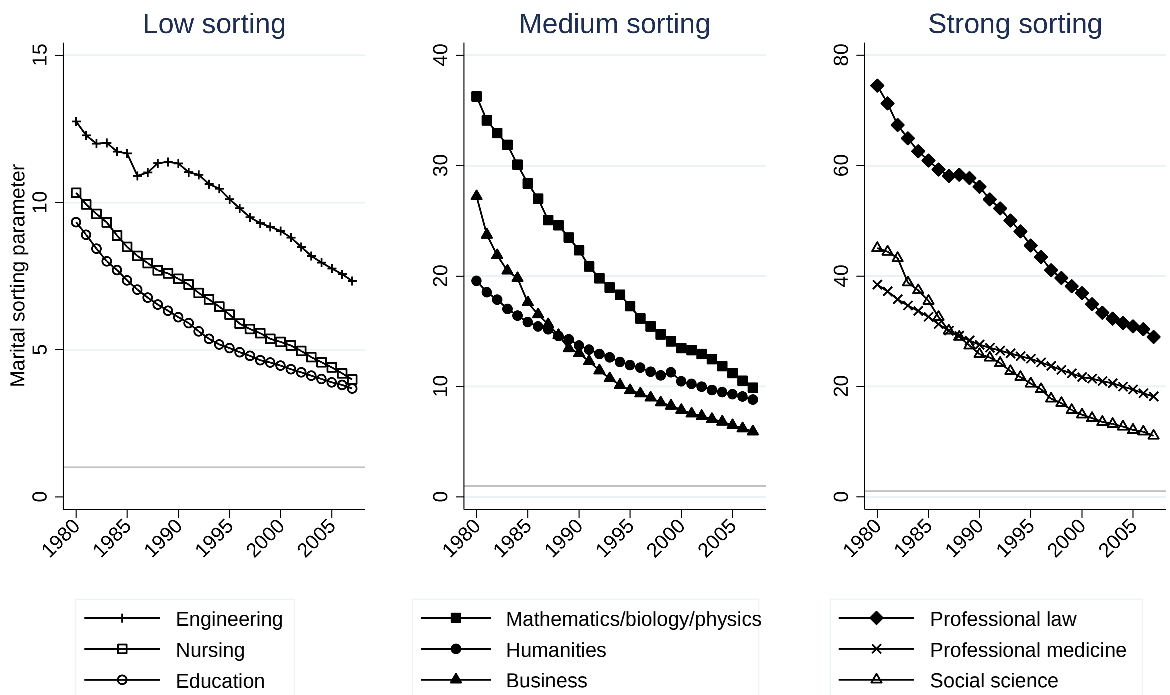
Table 2: Aggregate Measures of Marital Sorting

	U.S.		Norway	
	1980	2007	1980	2007
Weighted average of marital sorting parameters along the diagonal	1.93	1.97	1.45	1.55

Notes: This table reports weighted averages of the marital sorting parameters reported in Appendix Table A.3. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

Assortative mating by college major. The rich Norwegian data allows us to bring evidence on assortative mating by college major. This is done by splitting the college category into nine mutually exclusive sub-categories by field of study. Panels A and B of Appendix Table A.4 report the full set of marital sorting parameters, while Figure 5 displays the sorting parameters for the same college majors of husbands and wives. This figure reveals that assortative mating is much stronger by college major than by education level. The assortativeness is strongest for law and medicine, the fields with the highest economic returns. In 1980, for example, a graduate in medicine was 38 times as likely to be married to a college graduate with a medical degree, compared to the counterfactual situation where spouses were randomly matched. By comparison, college graduates as a whole were only 4.4 times as likely to be married to one another as compared to the probability with random mating. The assortative mating by college major declines over time but remains sizeable. In 2007, graduates in medicine were still 18 times as likely to be married to one another, relative to the probability under random matching. Taken together, these findings suggest that the choice of college major is an important but neglected pathway through which individuals sort into internally homogenous marriages.

Figure 5: Trends in Marital Sorting by College Major in Norway, 1980-2007



Notes: This figure displays the time trends in marital sorting parameters for which husbands and wives have the same college major. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years.

4. Determinants of Household Income Inequality

Decomposition method. To quantify the contribution to household income inequality of changes in returns to education, educational composition and educational assortative mating, we adopt the decomposition method proposed by DiNardo, Fortin, and Lemieux (1996). This approach produces income distributions under counterfactual scenarios where the distribution of one factor is fixed at a base year, while the other factors vary over time.

Consider the joint distribution of household income and couples' education in year t, $F_{Y,X}(y,x\,|\,t)$, where y denotes household income, and x denotes the couples' educational attainment, consisting of the (i, j) combination of the husband's and the wife's education. The distribution of income in year t is given by:

(2) $$F_Y(y \mid t) = \int F_{Y|X}(y \mid x, t) dF_X(x \mid t),$$

where $F_{Y|X}(y \mid x, t)$ is the conditional distribution of income for couples with education x in year t (i.e. the returns to education) and $F_X(x \mid t)$ is the joint distribution of spouses' education in year t.

To define the counterfactual scenarios, let t_{ij} denote the year in which the couples' educational attainment are measured, t_s denote the year the marital sorting parameters are measured, and t_y denote the year in which the economic returns are measured. Depending on when we measure these three factors, we obtain different counterfactual scenarios. In general, the income distribution under a counterfactual scenario is given by:

(3) $$\tilde{F}_Y(y \mid t_y, t_{ij}, t_s) = \int F_{Y|X}(y \mid x, t_y) \psi_x(x \mid t_y, t_{ij}, t_s) dF_X(x \mid t_y)$$

where ψ_x is a re-weighting function defined as

$$\psi_x(x \mid t_y, t_{ij}, t_s) = \frac{d\tilde{F}_X(x \mid t_{ij}, t_s)}{dF_X(x \mid t_y)},$$

for which $\tilde{F}_X(x \mid t_{ij}, t_s)$ denotes the joint distribution of spouses' education that would have occurred if the couples' educational attainment are measured in t_{ij} and the marital sorting parameters are measured in t_s.

In the empirical analysis, we hold the distribution of one factor fixed at base year t_0, while we let the distributions of the other factors vary over time. For example, $\tilde{F}_Y(y \mid t_y = t, t_{ij} = t, t_s = t_0)$ represents the income distribution in a scenario where the returns to education and the educational composition are measured in year *t*, whereas the marital sorting parameters are measured in year t_0. By comparing this counterfactual income distribution to the actual income distribution in year t, we may assess how household income inequality is affected by changes in educational assortative mating between year t_0 and t.

To obtain the counterfactual income distribution, we estimate the reweighting function as

$$\psi'_x(x \mid t_y = t, t_{ij} = t, t_s = t_0) = \frac{\tilde{p}_x(t_{ij} = t, t_s = t_0)}{p_x(t_y = t)} \tag{4}$$

where $p_x(t_y = t)$ denotes the proportion of couples with educational attainment x in year t, whereas $\tilde{p}_x(t_{ij} = t, t_s = t_0)$ denotes the proportion of couples who would have had educational attainment x if the marginal distributions of education among husbands and wives are measured in year t but couples are formed according to the marital sorting parameters of year t_0. In Appendix B, we describe the stochastic matching procedure we use to estimate $\tilde{p}_x(t_{ij} = t, t_s = t_0)$.

In the same manner, we construct income distributions under alternative counterfactual scenarios, including keeping the education distribution of husbands and wives or the economic returns to education fixed at base year t_0. Similarly, when examining the factors behind the difference in household income inequality in the U.S. compared to Norway, we replace the distribution of one factor in a given year with the corresponding distribution in the other country in the same year.

Assortative mating and household income inequality. Figure 6 graphs household income inequality over time in the U.S. (Panel A) and in Norway (Panel B).[9] This figure measures inequality according to the Gini coefficient. The solid lines show the growth in household income inequality, while the dashed lines give the time trends in household income inequality for a counterfactual scenario in which all marital sorting parameters are set equal to one; this means that men and women with the same level of education

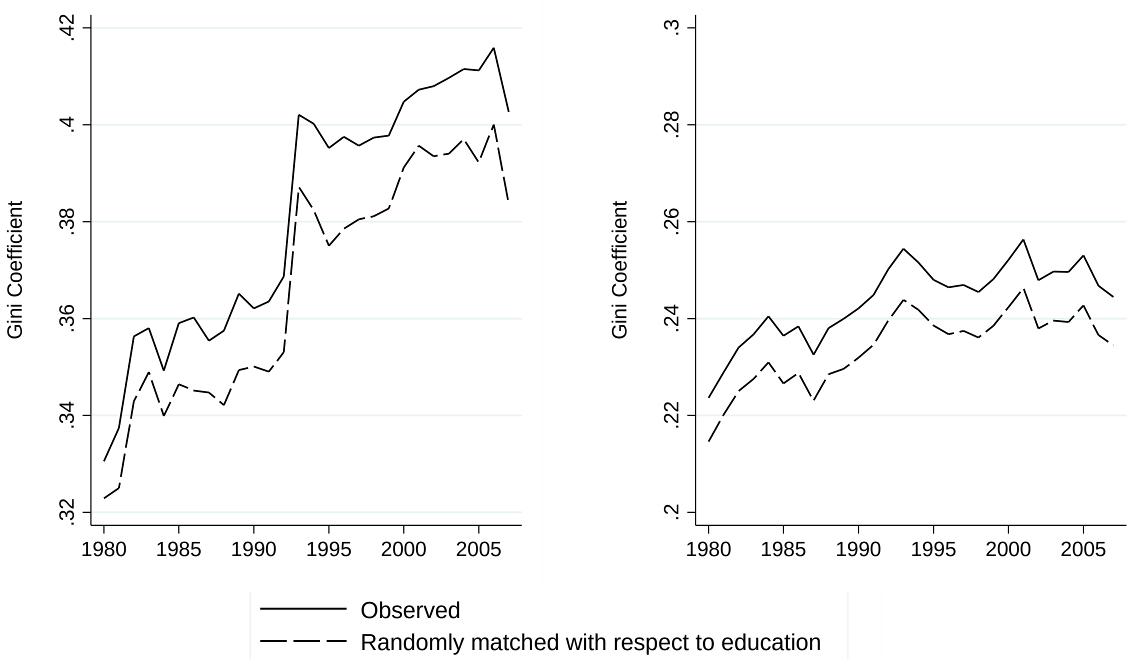
[9] The spike in inequality in 1993 is due to changes in the processing of the March CPS earnings questions between 1992 and 1993.

marry as frequently as what would be expected under a marriage pattern that is random in terms of education.

As expected, assortative mating leads to an increase in household income inequality in both countries. In the U.S., for example, educational assortative matching increased the Gini coefficient in 2007 from 0.384 to 0.403. Put into perspective, this 5 percent increase in the Gini coefficient corresponds to introducing an equal-sized lump sum tax of 5 percent of the mean household income and redistributing the derived tax as proportional transfers where each household receives 5 percent of its income (Aaberge, 1997). This hypothetical tax-transfer intervention illustrates that educational assortative mating has a non-negligible impact on the distribution of household income in the U.S.

Figure 6: Household Income Inequality and Marital Sorting

Panel A: Marital Sorting, U.S. | Panel B: Marital Sorting, Norway



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dashed lines show the Gini coefficient in a counterfactual scenario where we in each year match husbands and wives randomly with respect to education.

Appendix Table A.5 complements this evidence by showing how assortative mating affected different parts of the distribution of household income. The 90/10 measures the ratio of income at the 90th percentile of the household income distribution to that of the 10th percentile, while the 90/50 and 50/10 ratios illustrate whether an increase in the 90/10 ratio is due to the rich getting richer or the poor getting poorer. We compare the percentile ratios in the actual distribution of household income to those that would have occurred if husbands and wives are randomly matched with respect to education. The results suggest that assortative mating matters most for inequality in the lower part of distribution, especially in the U.S.

Evolution in household income inequality. We now examine the importance of various factors for the time trends in household income inequality, including changes in educational assortative mating (Figure 7), returns to education (Figure 8), and educational composition (Figure 9).[10] Each figure compares the actual evolution of household income inequality to the counterfactual levels of inequality, where we hold the distribution of one factor fixed at its level in 1980 while we let the distributions of the other factors vary over time. We also show that the conclusions from the decomposition analysis are robust to whether we use 1980 or 2007 as the base year.

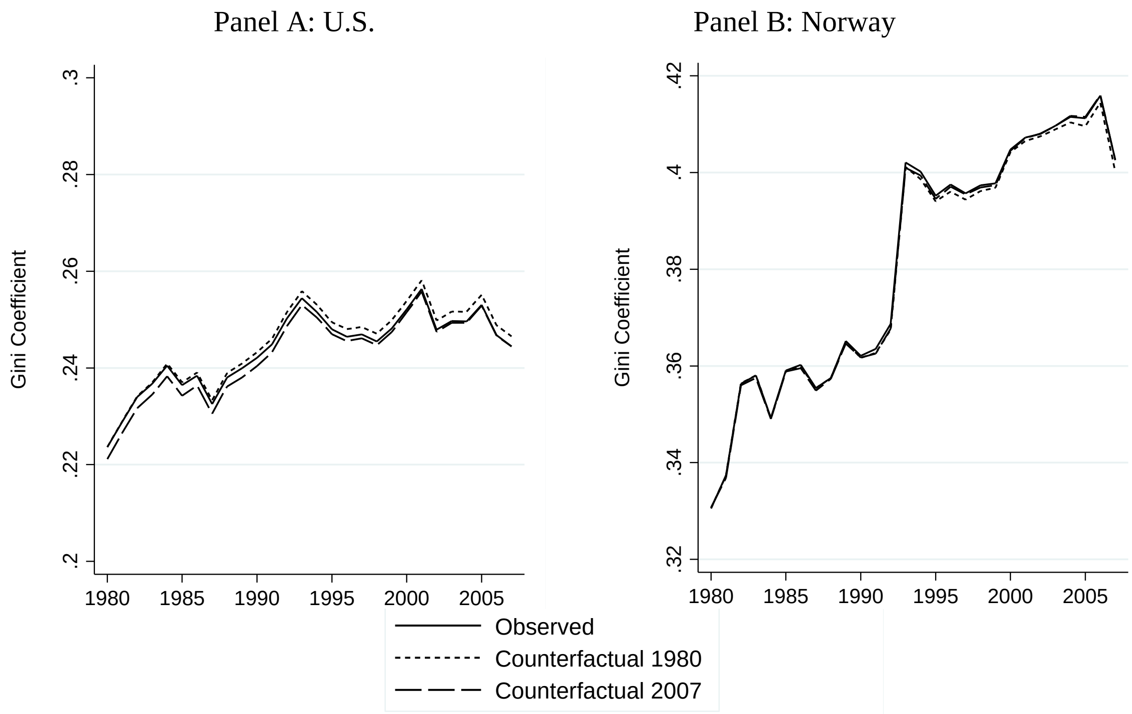
Figure 7 shows that changes in assortative mating over time matters little for the time trends in household income inequality. This finding refutes the widespread view that changes in assortative mating have led to a rise in household income inequality. In each year and for both countries, the Gini coefficients in the actual and the counterfactual distribution of household income barely differ.

By comparison, the increasing returns to education seem to be a key driver behind the rise in household income inequality. Figure 8 shows these results. For both countries, the decomposition analysis suggests the Gini coefficient in household income would have been steadily declining if the returns to

[10] In Appendix Tables A.5-A.7, we present decomposition results for different parts of the household income distribution. Taken together, the results suggest the lower part of the household income distribution has been most influenced by changes in education returns and composition. The tables also show that changes in assortative mating have little impact throughout the income distribution.

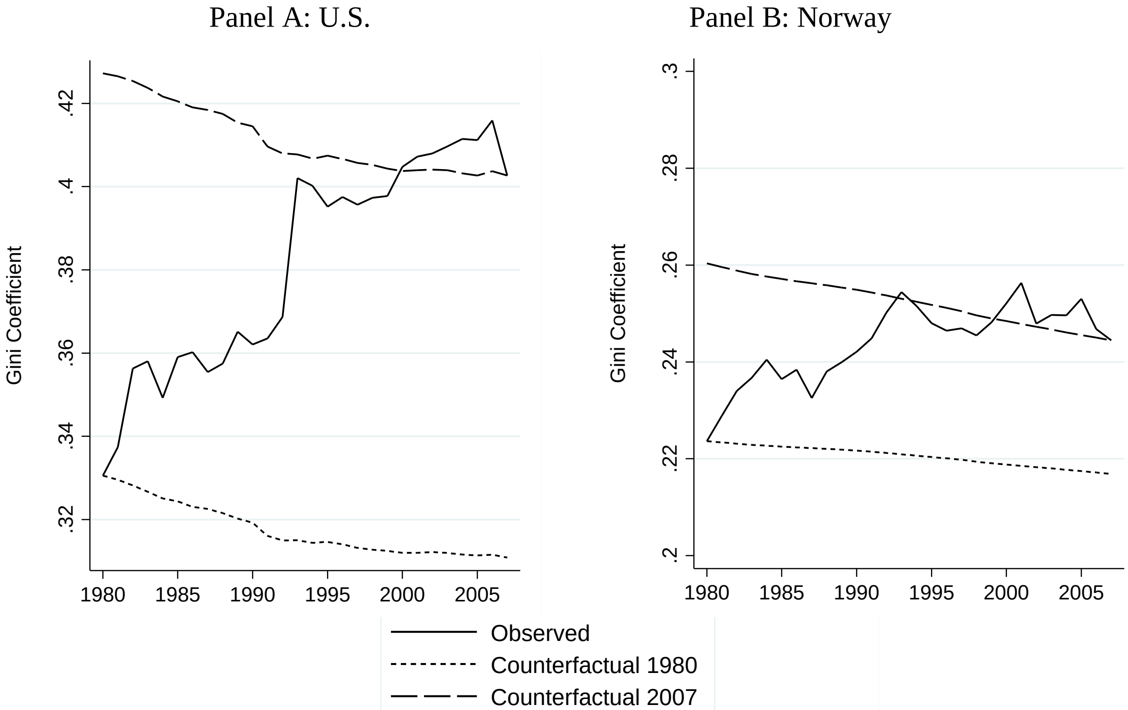
education remained at their levels in 1980. In the U.S., for example, the Gini coefficient in 2007 is predicted to be 23 percent lower in the absence of changes to the returns to education. This reduction in the Gini coefficient corresponds to introducing a 23 percent proportional tax on income and then redistributing the derived tax revenue as equal sized amounts to the households (Aaberge, 1997). This finding suggests that changes in the returns to education are not only important in explaining the growth in income inequality among males (see e.g. Autor, Katz and Kearney, 2008; Acemoglu and Autor, 2010), but also a key factor behind the rise in household income inequality over the past few decades. Appendix Table A.6 demonstrates that the lower part of the household income distribution has been most influenced by changes in education returns. For example, if the returns to education remained at their levels in 1980, we estimate that the 50/10 ratio would have been 22 percent lower in 2007 (a reduction from 3.33 to 2.60), whereas the 90/50 ratio would have been 14 percent lower (a reduction from 2.15 to 1.85).

Figure 7: Household Income Inequality and Changes in Marital Sorting



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted (dashed) lines show the Gini coefficient in a counterfactual scenario where the marital sorting parameters are kept fixed at their levels in 1980 (2007), while we let the distributions of the other factors vary over time.

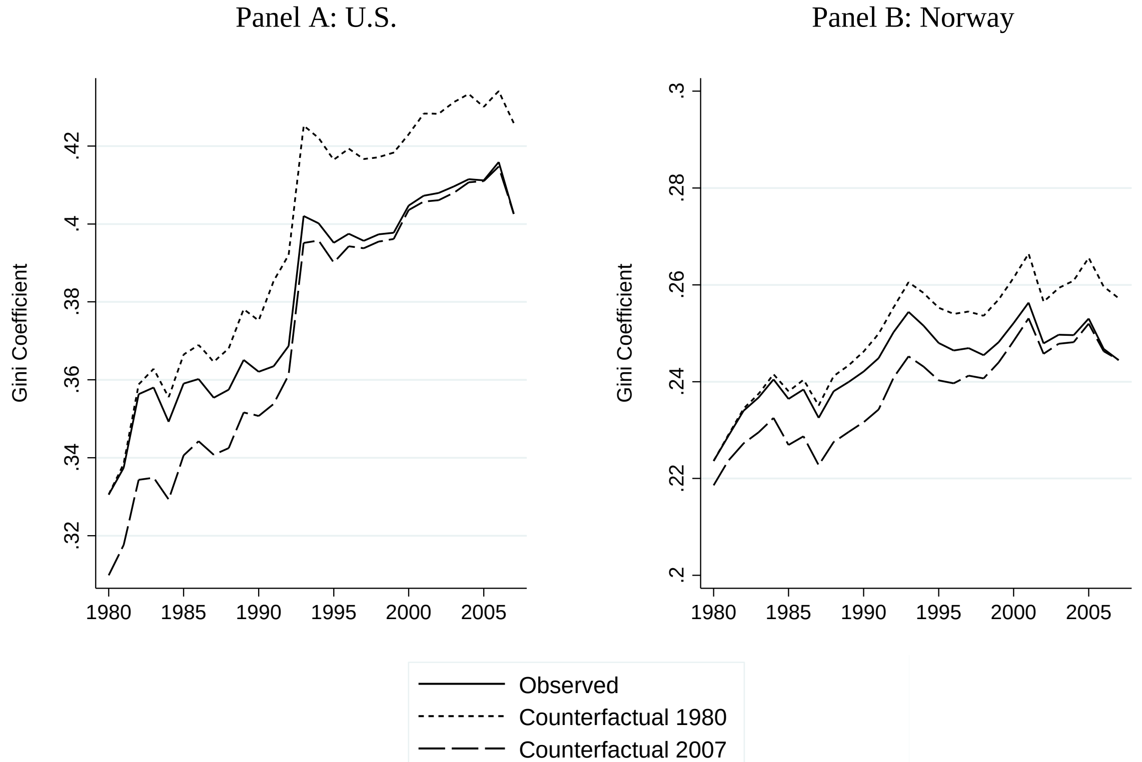
Figure 8: Household Income Inequality and Changes in Returns to Education



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted (dashed) lines show the Gini coefficient in a counterfactual scenario where the returns to education are kept fixed at their levels in 1980 (2007), while we let the distributions of the other factors vary over time.

Figure 9 shows that changes in the educational composition offset some of the increase in household income inequality. The decomposition results suggest that both countries would have experienced a sharper rise in inequality if the education distributions of husbands and wives were as in 1980. For instance, we find that the Gini coefficient in 2007 would have been 6 (5) percent higher in the U.S. (Norway) in the absence of the changes in educational composition. These compositional effects are distinct from the standard price effects that are often invoked to explain changes in inequality (see e.g. Juhn, Murphy and Pierce, 1993; Lemieux, 2006). Holding returns to education constant, changes in education composition can mechanically raise or lower income inequality by changing the share of households that have more or less dispersed income. Furthermore, compositional changes can affect household income inequality by increasing or reducing heterogeneity across households in education levels.

Figure 9: Household Income Inequality and Changes in Educational Composition



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted (dashed) lines show the Gini coefficient in a counterfactual scenario where the education distributions of husbands and wives are kept fixed at their levels in 1980 (2007), while we let the distributions of the other factors vary over time.

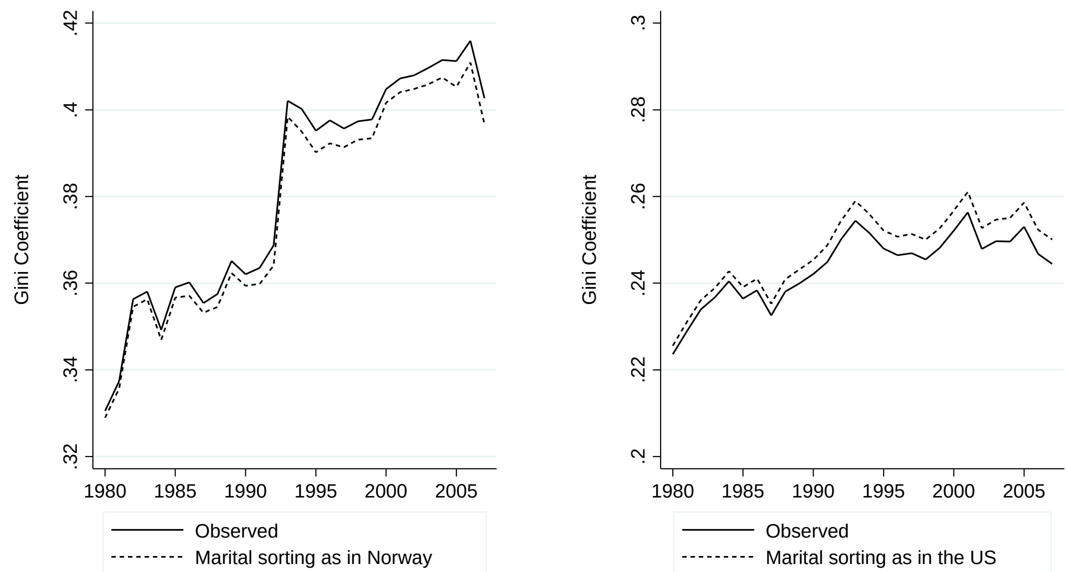
Cross-country differences in inequality. Figures 10-12 examine factors behind the difference in household income inequality between the U.S. and Norway.[11] In each year, the counterfactual level of inequality is computed by replacing the distribution of one factor in a given country with the corresponding distribution in the other country. Figure 10 shows the relatively high levels of inequality in the U.S. cannot be explained by differences in assortative mating. By comparison, the high returns to education in the U.S account for much of the cross-country difference in inequality: The decomposition results in Figure 11 suggest that the Gini coefficient in the U.S. would be reduced by as much as 41 percent if the returns to education were as in Norway in 2007. Lastly, Figure 12 suggests the relatively

[11] In Appendix Table A.8, we present decomposition results for different parts of the household income distribution in Norway and the U.S. The results suggest that differences in the lower part of the household income distributions have been most influenced by differences in education returns and composition across the two countries.

high level of inequality in the U.S. is mitigated somewhat by its education composition: When imposing the education distribution of husbands and wives in Norway, we find that the Gini coefficient increases by somewhere between 4 and 10 percent over the period 1980-2007.

Figure 10: Household Income Inequality and Cross-Country Differences in Marital Sorting

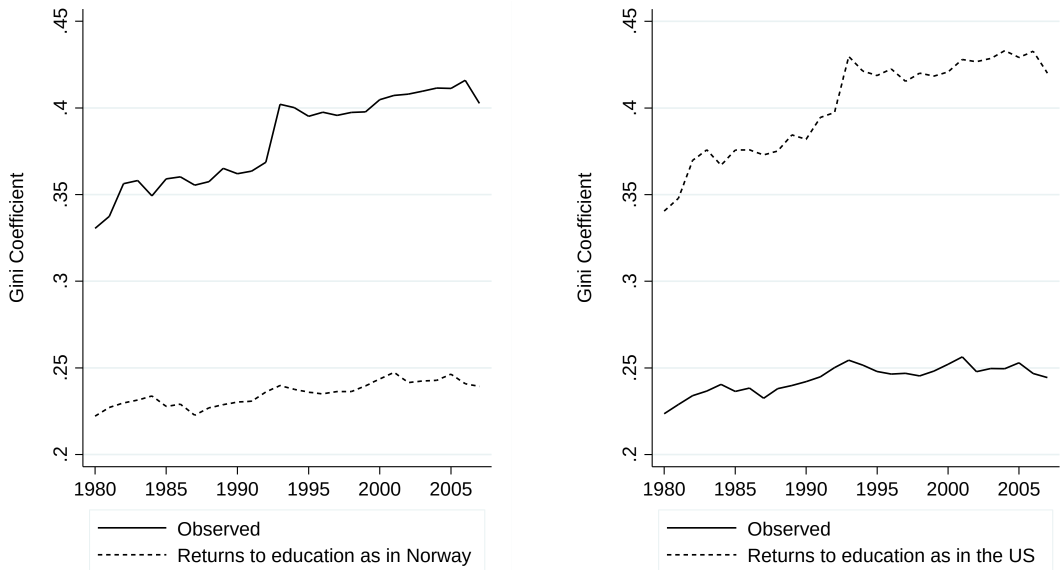
Panel A: U.S. Panel B: Norway



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted lines show the Gini coefficient in a counterfactual scenario where we in each year replace the marital sorting parameters in one country with the marital sorting parameters in the other country.

Figure 11: Household Income Inequality and Cross-Country Differences in Education Returns

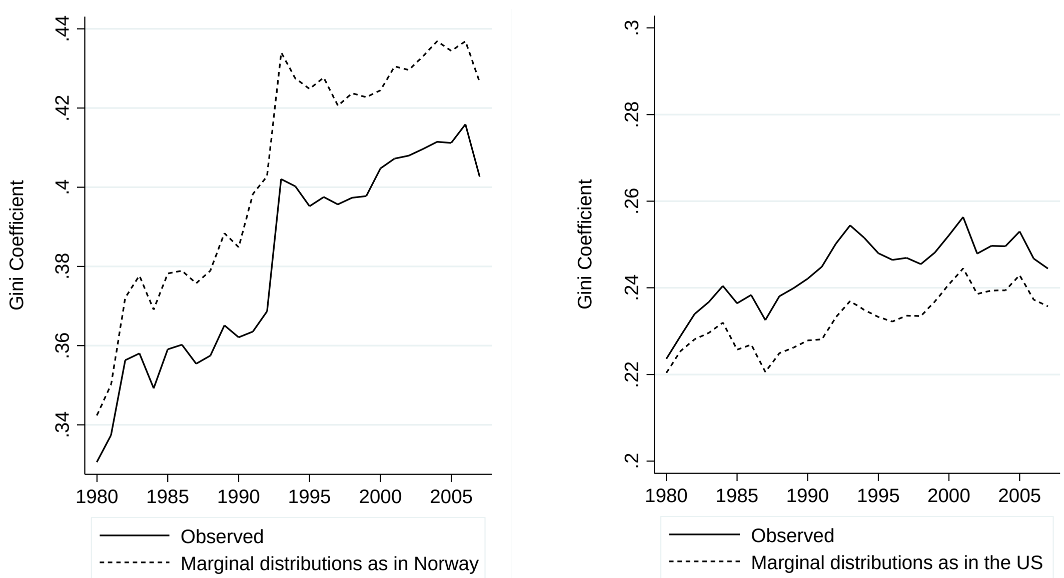
Panel A: U.S. Panel B: Norway



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted lines show the Gini coefficient in a counterfactual scenario where we in each year replace the returns to education in one country with the returns to education in the other country.

Figure 12: Household Income Inequality and Cross-Country Differences in Education Composition

Panel A: U.S. Panel B: Norway



Notes: This figure displays actual and counterfactual time trends in household income inequality. In each year, we consider couples where the mean of the husband's and wife's age is between 26 and 60 years. The solid lines show the Gini coefficient in the actual distribution of household income. The dotted lines show the Gini coefficient in a counterfactual scenario where we in each year replace the distributions of education of husbands and wives in one country with the distributions of education of husbands and wives in the other country.

Robustness analysis. We have performed several specification checks to examine the robustness of the decomposition results. We first use the rich Norwegian dataset to assess how accounting for heterogeneity by college major affects the evidence on the determinants of household income inequality. Appendix Figure A.1 shows that the conclusions about the evolution of household income inequality in Norway hold: Changes in educational composition and returns to education remain the key factors, while educational assortative mating continues to play a minor role. This finding is reassuring given that one cannot link spouses in the U.S. data on post-secondary fields of study.

We next examine the sensitivity of the results to accounting for age in the measurement of marital sorting. In particular, we characterize each individual by both their educational level and their age group. For each gender, we use four individual age groups (<35; 35-44; 45-54; >54) in addition to the four educational levels. The sample is thus divided into 256 groups on the basis of the husbands' and wives' educational attainment and age. By comparison, the baseline specification where we abstracted from age gives 16 groups. Except for the additional groups, we use the same decomposition method as outlined above. Appendix Figure A.2 shows that the decomposition results barely move when we account for age in the measurement of marital sorting.

Finally, we check if our results are robust to accounting for changes over time in the likelihood of getting married according to the education of males and females. Appendix C provides the details of this robustness check. We begin by extending the sample used to estimate the marital sorting parameters to include single women and men aged 26–60. This allows us to characterize each individual by their educational level, gender and marital status. In each year and for every level of education, this adds another gender-specific sorting parameter which represents not being married.

The next step is to estimate the counterfactual income distribution while accounting for changes in the probability of marriage by education level. For this purpose, we use the new set of sorting parameters to re-estimate $\tilde{p}_x(t_{ij} = t, t_s = t_0)$, capturing also changes (between base year t_0 and year t) in the probability of being married by gender and education. After estimating $\tilde{p}_x(t_{ij} = t, t_s = t_0)$, we obtain the counterfactual income distribution from the reweighting function given in equation (4). To directly compare the robustness check to the main results, we exclude singles in the measurement of the actual and counterfactual income distributions.

The results from this robustness check are presented in Appendix Figure A.3. It is reassuring to find that accounting for changes in the probability of being married by education level do not affect our conclusion: Changes in assortative mating over time barely move the time trends in household income inequality.

5. Conclusion

In this paper, we investigated the pattern of educational assortative mating, its evolution over time, and its impact on household income inequality. To these ends, we used rich data from the U.S. and Norway over the period 1980-2007. We found evidence of positive assortative mating at all levels of education in both countries. However, the time trends vary by the level of education: Among college graduates, assortative mating has been declining over time, whereas low educated are increasingly sorting into internally homogenous marriages. When looking within the group of college educated, we find strong but declining assortative mating by academic major.

These findings motivated and guided a decomposition analysis, where we quantified the contribution of various factors to the distribution of household income. We found that educational assortative mating accounts for a non-negligible part of the cross-sectional inequality in household income. However, the changes in assortative mating over time barely moved the time trends in household income inequality. This is because the decline in assortative mating among the highly educated was offset by an increase in assortative mating among the low educated. By comparison, increases in the returns to education generated a considerable rise in household income inequality, but these price effects were partly mitigated by increases in college attendance and completion rates among women.

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Appendix A: Additional Tables and Figures

Table A.1: Income Differentials by Education Level

	U.S.				Norway			
	1980		2007		1980		2007	
	Wives	Husbands	Wives	Husbands	Wives	Husbands	Wives	Husbands
Intercept	6350 (520)	1207 (1105)	-2995 (1134)	-5374 (2183)	888 (61)	12564 (85)	4099 (134)	12788 (235)
Potential experience	202 (44)	2770 (82)	970 (93)	3124 (169)	530 (5)	1162 (6)	1417 (11)	2283 (17)
Potential experience squared	-5 (1)	-50 (1)	-17 (2)	-61 (3)	-9 (0)	-22 (0)	-28 (0)	-45 (0)
High school graduates	4291 (238)	12876 (507)	9225 (418)	12195 (786)	2017 (24)	3752 (31)	5866 (53)	7023 (85)
Some college	7309 (359)	20170 (657)	16233 (496)	21042 (805)	6943 (66)	10610 (55)	12869 (99)	17995 (126)
College graduates	13170 (447)	42921 (798)	34151 (678)	62178 (1192)	11357 (50)	15762 (58)	18148 (67)	24503 (118)
Mean	13275	50605	27739	59627	9440	29177	28502	48168
N	28565	28565	32127	32127	655032	655032	520107	520107
R-squared	0.0613	0.2009	0.1006	0.1464	0.1123	0.2036	0.1725	0.1603

Notes: This table reports OLS estimates of annual income on education level and potential experience (linearly and squared). Each column is a separate regression. Potential experience is defined as age - years of education - 6. Excluded education level is no high school degree. Dependent variable is the annual income in USD-2007. Standard errors in parentheses.

Table A.2: Income Differentials by Education Level and Field of Study, for Norway

	1980		2007	
	Wives	Husbands	Wives	Husbands
Intercept	411	12329	1333	10558
	(60)	(81)	(140)	(247)
Potential experience	568	1181	1594	2401
	(5)	(6)	(11)	(18)
Potential experience squared	-10	-23	-30	-47
	(0)	(0)	(0)	(0)
High school graduates	2041	3753	5950	7121
	(24)	(32)	(59)	(96)
Some college	7033	10622	13104	18177
	(55)	(50)	(85)	(121)
Post-secondary degree in:				
Education	12108	7327	14602	6623
	(63)	(87)	(85)	(185)
Nursing	8689	9386	13837	8713
	(58)	(272)	(86)	(296)
Humanities	12668	12136	16382	11366
	(131)	(118)	(144)	(241)
Social science	18730	15252	23075	21376
	(346)	(194)	(215)	(274)
Mathematics/biology/physics	19683	16479	28764	26384
	(310)	(129)	(209)	(227)
Engineering	13865	19693	30142	32353
	(326)	(99)	(212)	(172)
Business	16738	19845	28068	35754
	(407)	(146)	(148)	(198)
Professional law	21944	20701	31485	35963
	(418)	(174)	(263)	(345)
Professional medicine	26866	27564	43523	49974
	(198)	(125)	(200)	(276)
Mean	9440	29177	28502	48168
N	655032	655032	520107	520107
R-squared	0.1268	0.2332	0.2294	0.2146

Notes: This table reports OLS estimates of annual income on education level, field of study, and potential experience (linearly and squared). Potential experience is defined as age - years of education - 6. Excluded education level is no high school degree. Dependent variable is the annual income in 2007 USD. Standard errors in parentheses.

Table A.3: Marital Sorting Parameters in Norway and the U.S., 1980 and 2007

U.S.

1980

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates
No high school degree	2.74	0.80	0.38	0.09
High school graduates	0.83	1.46	1.02	0.50
Some college	0.29	0.67	1.75	1.54
College graduates	0.08	0.30	0.83	2.98

2007

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates
No high school degree	6.37	0.97	0.34	0.09
High school graduates	1.12	1.89	0.83	0.35
Some college	0.46	0.92	1.68	0.72
College graduates	0.12	0.36	0.75	1.94

Norway

1980

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates
No high school degree	1.60	0.88	0.44	0.16
High school graduates	0.71	1.21	1.21	0.82
Some college	0.14	0.67	2.48	3.72
College graduates	0.19	0.66	1.71	4.35

2007

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates
No high school degree	1.96	1.15	0.62	0.27
High school graduates	1.10	1.25	0.91	0.49
Some college	0.56	0.78	1.63	1.34
College graduates	0.35	0.63	1.17	2.07

Table A.4. Panel A: Marital Sorting Parameters with Field of Study in Norway, 1980

Husbands' Education / Wives' Education	No high school degree	High school graduates	Some college	Education	Nursing	Humanities	Social science	Mathematics/ Biology/ physics	Engineering	Business	Professional law	Professional medicine
No high school degree	1.60	0.88	0.44	0.23	0.24	0.11	0.18	0.12	0.16	0.17	0.11	0.09
High school graduates	0.71	1.21	1.21	0.83	0.71	0.63	0.84	0.85	0.95	1.00	0.85	0.63
Some college	0.14	0.67	2.48	2.36	2.08	4.35	4.24	3.98	4.19	4.75	5.06	3.72
Education	0.16	0.56	1.77	9.33	1.42	4.90	3.06	3.70	3.21	2.29	2.58	2.79
Nursing	0.27	0.89	1.82	1.79	10.33	2.88	2.47	2.89	2.74	2.23	2.63	5.75
Humanities	0.07	0.31	1.38	1.97	1.77	19.57	9.13	5.91	5.23	5.19	6.97	5.58
Social science	0.06	0.16	1.46	2.17	0.64	9.75	45.08	5.00	3.77	7.17	7.55	8.74
Mathematics/ biology/physics	0.04	0.17	0.75	0.56	1.54	5.87	2.33	36.28	11.02	2.72	2.70	3.90
Engineering	0.02	0.26	1.29	1.19	1.14	5.59	1.72	20.79	12.76	3.18	4.84	6.03
Business	0.14	0.62	1.65	1.38	0.89	2.54	7.17	2.30	3.09	27.24	6.11	2.66
Professional law	0.06	0.23	1.08	0.43	0.94	5.03	6.63	3.45	2.47	6.02	74.53	5.07
Professional medicine	0.03	0.22	0.98	0.93	2.51	5.07	4.95	5.37	3.53	2.97	5.92	38.44

Table A.4. Panel B: Marital Sorting Parameters with Field of Study in Norway, 2007

Husbands' Education / Wives' Education	No high school degree	High school graduates	Some college	Education	Nursing	Humanities	Social science	Mathematics/ Biology/ physics	Engineering	Business	Professional law	Professional medicine
No high school degree	1.96	1.15	0.62	0.33	0.29	0.22	0.28	0.24	0.30	0.27	0.13	0.16
High school graduates	1.10	1.25	0.91	0.61	0.52	0.32	0.47	0.47	0.53	0.54	0.36	0.26
Some college	0.56	0.78	1.63	0.95	0.93	1.39	1.42	1.33	1.46	1.77	1.57	1.06
Education	0.38	0.74	1.18	3.69	1.43	1.87	1.41	1.56	1.47	1.31	1.13	1.19
Nursing	0.45	0.78	1.25	1.35	3.98	1.37	1.66	1.45	1.52	1.36	1.32	2.49
Humanities	0.27	0.38	1.14	1.49	1.31	8.81	2.79	2.37	2.03	1.69	2.41	2.83
Social science	0.17	0.31	1.10	0.98	1.56	4.00	11.07	2.41	2.23	2.28	3.89	2.34
Mathematics/ biology/physics	0.19	0.40	0.87	0.69	0.54	1.27	1.36	9.90	4.32	1.51	1.34	1.72
Engineering	0.19	0.36	0.90	0.63	0.42	1.30	1.27	4.89	7.34	1.65	1.05	1.14
Business	0.31	0.58	1.32	0.81	0.89	1.07	1.81	1.66	1.84	5.92	2.51	0.99
Professional law	0.14	0.30	1.02	0.55	0.85	1.50	2.89	1.85	1.53	3.37	28.98	2.29
Professional medicine	0.16	0.26	0.83	0.87	1.77	2.76	2.38	2.56	2.25	1.86	3.09	18.18

Table A.5: Trends in Household Income Inequality and (Changes in) Marital Sorting

		U.S.		Norway	
		1980	2007	1980	2007
Gini coefficient	Observed	0.3306	0.4027	0.2236	0.2444
	Randomly matched with respect to education	0.3229	0.3837	0.2146	0.2345
	Counterfactual 1980	-	0.4003	-	0.2465
	Counterfactual 2007	0.3308	-	0.2212	-
90/10 Percentile ratio	Observed	5.69	7.18	2.72	3.22
	Randomly matched with respect to education	5.45	6.25	2.62	3.03
	Counterfactual 1980	-	7.05	-	3.26
	Counterfactual 2007	5.76	-	2.69	-
90/50 Percentile ratio	Observed	1.85	2.15	1.55	1.64
	Randomly matched with respect to education	1.80	2.07	1.52	1.60
	Counterfactual 1980	-	2.15	-	1.64
	Counterfactual 2007	1.85	-	1.54	-
50/10 Percentile ratio	Observed	3.07	3.33	1.76	1.97
	Randomly matched with respect to education	3.02	3.02	1.73	1.89
	Counterfactual 1980	-	3.27	-	1.99
	Counterfactual 2007	3.11	-	1.75	-

Table A.6: Trends in Household Income Inequality and Changes in Returns to Education

		U.S.		Norway	
		1980	2007	1980	2007
Gini coefficient	Observed	0.3306	0.4027	0.2236	0.2444
	Counterfactual 1980	-	0.3108	-	0.2169
	Counterfactual 2007	0.4272	-	0.2603	-
90/10 Percentile ratio	Observed	5.69	7.18	2.72	3.22
	Counterfactual 1980	-	4.80	-	2.66
	Counterfactual 2007	8.67	-	3.67	-
90/50 Percentile ratio	Observed	1.85	2.15	1.55	1.64
	Counterfactual 1980	-	1.85	-	1.53
	Counterfactual 2007	2.28	-	1.59	-
50/10 Percentile ratio	Observed	3.07	3.33	1.76	1.97
	Counterfactual 1980	-	2.60	-	1.75
	Counterfactual 2007	3.80	-	2.31	-

Table A.7: Trends in Household Income Inequality and Changes in Educational Composition

		U.S.		Norway	
		1980	2007	1980	2007
Gini coefficient	Observed	0.3306	0.4027	0.2236	0.2444
	Counterfactual 1980	-	0.4259	-	0.2572
	Counterfactual 2007	0.3098	-	0.2186	-
90/10 Percentile ratio	Observed	5.69	7.18	2.72	3.22
	Counterfactual 1980	-	8.67	-	3.59
	Counterfactual 2007	4.80	-	2.69	-
90/50 Percentile ratio	Observed	1.85	2.15	1.55	1.64
	Counterfactual 1980	-	2.28	-	1.58
	Counterfactual 2007	1.85	-	1.53	-
50/10 Percentile ratio	Observed	3.07	3.33	1.76	1.97
	Counterfactual 1980	-	3.80	-	2.27
	Counterfactual 2007	2.60	-	1.76	-

Table A.8: Cross-Country Comparison. Evolution of Household Income Inequality

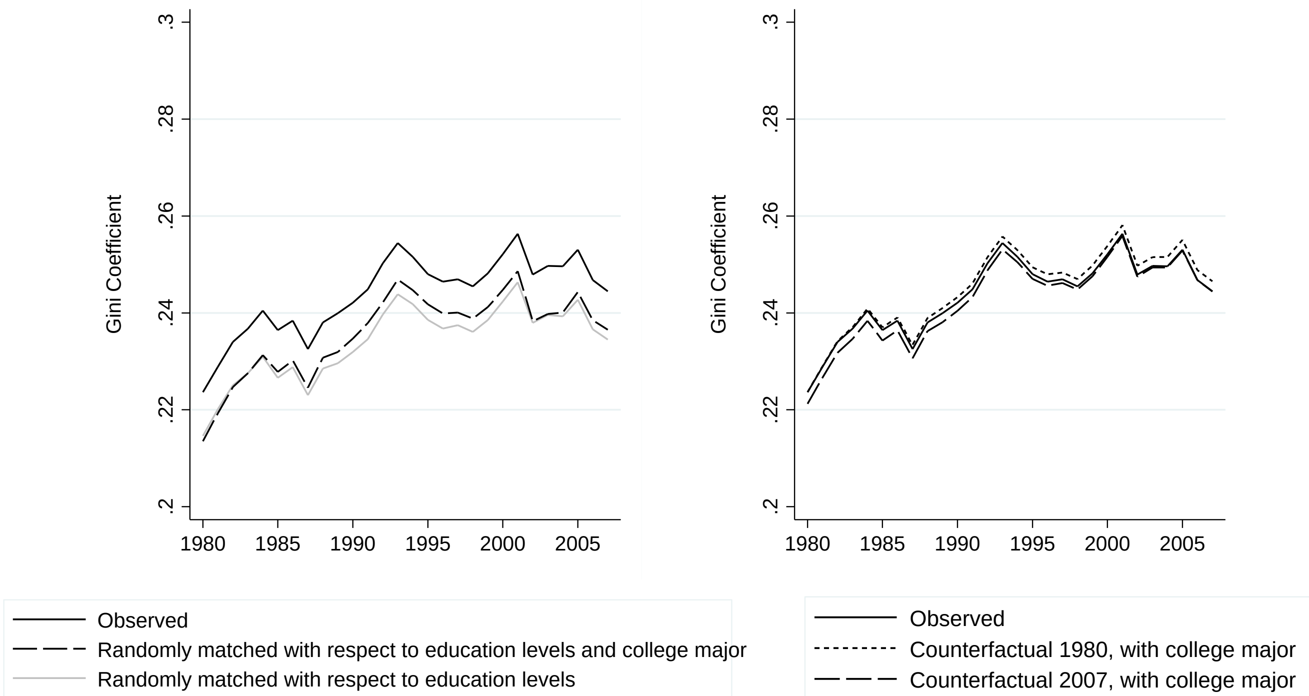
		1980	1990	2000	2007
Panel A: Imposing marital sorting of the other country					
Gini coefficient	Observed U.S.	0.3306	0.3621	0.4047	0.4027
	Marital sorting as in Norway	0.3289	0.3594	0.4016	0.3967
	Observed Norway	0.2236	0.2421	0.2521	0.2444
	Marital sorting as in the U.S.	0.2256	0.2454	0.2567	0.2501
90/10 Percentile ratio	Observed U.S.	5.69	6.44	6.68	7.18
	Marital sorting as in Norway	5.59	6.32	6.53	6.95
	Observed Norway	2.72	3.21	3.36	3.22
	Marital sorting as in the U.S.	2.74	3.27	3.46	3.34
90/50 Percentile ratio	Observed U.S.	1.85	2.00	2.08	2.15
	Marital sorting as in Norway	1.84	1.98	2.07	2.13
	Observed Norway	1.55	1.56	1.61	1.64
	Marital sorting as in the U.S.	1.56	1.57	1.63	1.65
50/10 Percentile ratio	Observed U.S.	3.07	3.23	3.21	3.33
	Marital sorting as in Norway	3.03	3.20	3.15	3.27
	Observed Norway	1.76	2.05	2.08	1.97
	Marital sorting as in the U.S.	1.76	2.08	2.13	2.02
Panel B: Imposing returns to education of the other country					
Gini coefficient	Observed U.S.	0.3306	0.3621	0.4047	0.4027
	Returns to education as in Norway	0.2222	0.2303	0.2436	0.2393
	Observed Norway	0.2236	0.2421	0.2521	0.2444
	Returns to education as in the U.S.	0.3405	0.3820	0.4208	0.4201
90/10 Percentile ratio	Observed U.S.	5.69	6.44	6.68	7.18
	Returns to education as in Norway	2.73	3.03	3.27	3.12
	Observed Norway	2.72	3.21	3.36	3.22
	Returns to education as in the U.S.	7.33	8.38	8.08	8.62
90/50 Percentile ratio	Observed U.S.	1.85	2.00	2.08	2.15
	Returns to education as in Norway	1.54	1.54	1.66	1.69
	Observed Norway	1.55	1.56	1.61	1.64
	Returns to education as in the U.S.	1.84	2.06	2.19	2.25
50/10 Percentile ratio	Observed U.S.	3.07	3.23	3.21	3.33
	Returns to education as in Norway	1.77	1.96	1.97	1.85
	Observed Norway	1.76	2.05	2.08	1.97
	Returns to education as in the U.S.	3.98	4.07	3.69	3.83

Panel C: Imposing educational composition of the other country					
Gini coefficient	Observed U.S.	0.3306	0.3621	0.4047	0.4027
	Educational composition as in Norway	0.3424	0.3848	0.4245	0.4265
	Observed Norway	0.2236	0.2421	0.2521	0.2444
	Educational composition as in the U.S.	0.2204	0.2279	0.2408	0.2357
90/10 Percentile ratio	Observed U.S.	5.69	6.44	6.68	7.18
	Educational composition as in Norway	7.50	8.46	8.23	8.97
	Observed Norway	2.72	3.21	3.36	3.22
	Educational composition as in the U.S.	2.70	2.98	3.21	3.05
90/50 Percentile ratio	Observed U.S.	1.85	2.00	2.08	2.15
	Educational composition as in Norway	1.86	2.08	2.23	2.33
	Observed Norway	1.55	1.56	1.61	1.64
	Educational composition as in the U.S.	1.54	1.54	1.66	1.68
50/10 Percentile ratio	Observed U.S.	3.07	3.23	3.21	3.33
	Educational composition as in Norway	4.04	4.07	3.69	3.85
	Observed Norway	1.76	2.05	2.08	1.97
	Educational composition as in the U.S.	1.76	1.94	1.94	1.81

Figure A.1. Household Income Inequality and Role of College Majors, Norway

Panel A: Role of Marital Sorting

Panel B: Role of Changes in Marital Sorting



Panel C: Role of Changes in Returns to Education

Panel D: Role of Educational Composition Changes

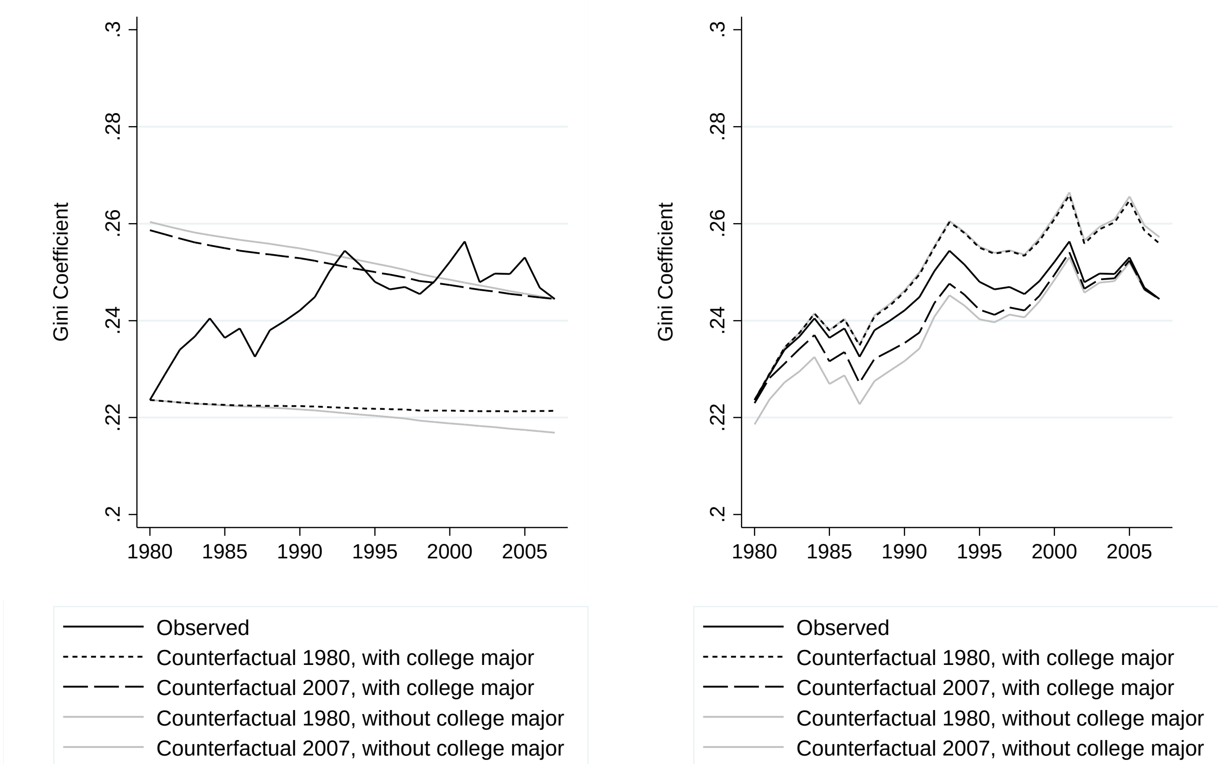


Figure A.2: Household Income Inequality and Changes in Marital Sorting

Taking Age into Account

Panel A: U.S. Panel B: Norway

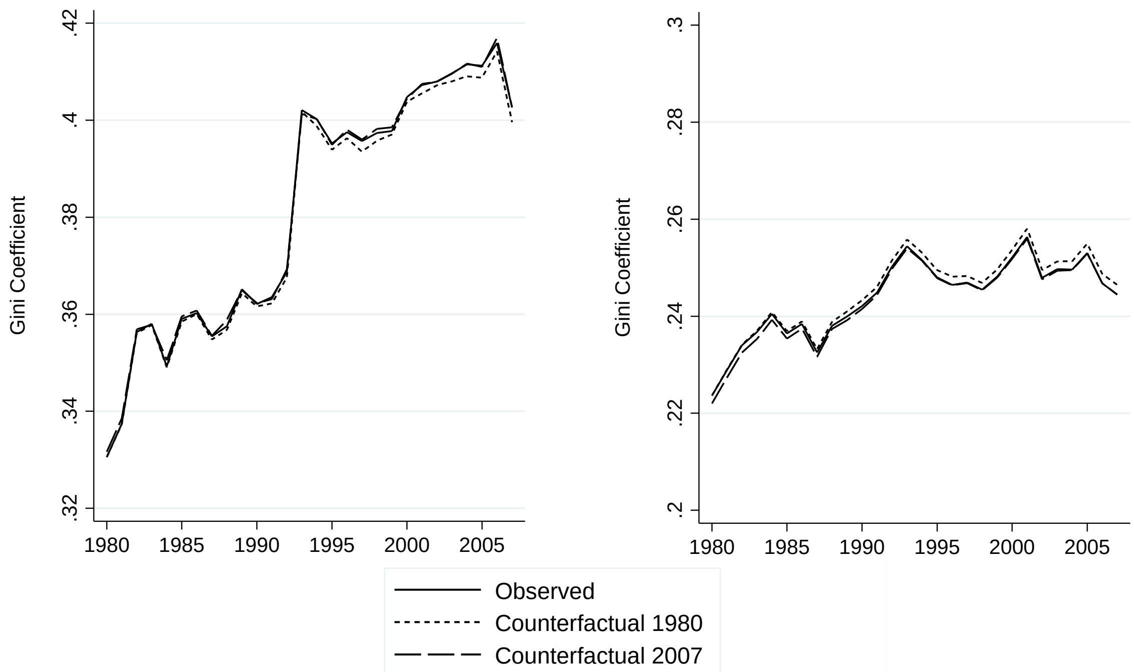
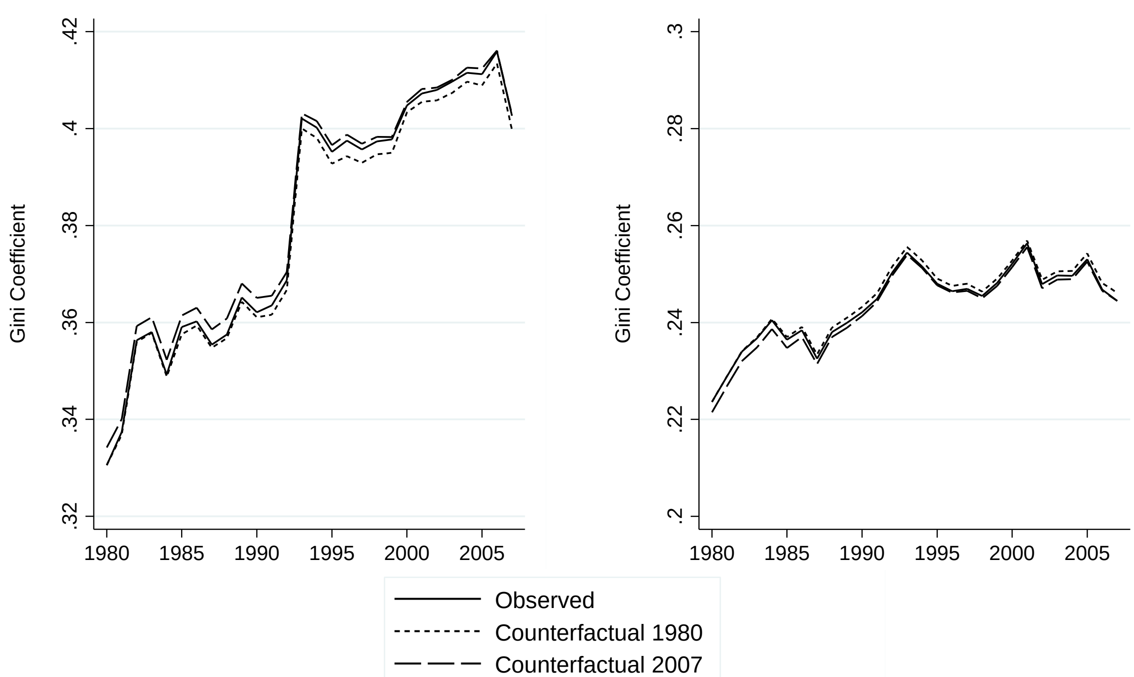


Figure A.3: Household Income Inequality and Changes in Marital Sorting

Taking the Probability of Marriage by Education into Account

Panel A: U.S. Panel B: Norway



Appendix B: Stochastic Matching Procedure

This appendix describes the stochastic matching procedure we use to estimate $\tilde{p}_x(t_{ij} = t, t_s = t_0)$, which is the proportion of couples who would have had educational attainment x if the marginal distributions of education among husbands and wives are measured in year *t* but couples are formed according to the marital sorting parameters of year t_0. Recall that the marital sorting parameter $s_{ij}(t_0)$ is defined as the actual probability of the match in year t_0 relative to the probability under random matching:

(A1) $$s_{ij}(t_0) = \frac{pr^{t_0}(wife = i \cap husband = j)}{pr^{t_0}(wife = i) \cdot pr^{t_0}(husband = j)}$$

The matching procedure takes two steps:

Step 1: Draw one wife and one husband from the marginal distribution of education for wives and husbands in period t

Step 2: With a probability proportional to $s_{ij}(t_0)$, the pair is matched and forms a couple. With the inverse probability, they remain unmatched.

We repeat these steps until all husbands and wives have achieved a match. At every iteration, we adjust the marginal distributions of husbands and wives by removing the pair if they form a couple. This gives an estimate of $\tilde{p}_x(t_{ij} = t, t_s = t_0)$.

We repeat the procedure until the average of the estimated $\tilde{p}_x(t_{ij} = t, t_s = t_0)$ stabilizes.

Appendix C: Robustness to changes in the probability of marriage by education level

This appendix describes how we account for changes in the probability of marriage by education level in the stochastic matching procedure we use to estimate $\tilde{p}_x(t_{ij} = t, t_s = t_0)$.

We first extend the sample to include single women and men aged 26–60. This allows us to characterize each individual by their educational level, gender and marital status. Appendix Table C.1 shows the distribution of education in the U.S. for singles and married couples by gender and education.

In each year and for every level of education, the inclusion of singles adds another gender-specific sorting parameter to be estimated, which represents not being married. Table C.2 shows the sorting parameters in the U.S.

We use the new set of sorting parameters and education distributions to re-estimate $\tilde{p}_x(t_{ij} = t, t_s = t_0)$. The new matching procedure takes the following two steps:

<u>Step 1:</u> Draw from the marginal distribution of education for females and males in period *t*.

<u>Step 2:</u> With a probability proportional to $s_{ij}(t_0)$, the pair is matched. With the inverse probability, they remain unmatched.

Each match can produce a couple, a single male, or a single female, depending on the draws made at the first step. For example, if a single is drawn from the distribution of education for females and a match is formed at the second step, the male is recorded as single.

We repeat these steps until all husbands and wives have achieved a match, either as single or in a couple. At every iteration, we adjust the marginal distributions of males and females by removing the pair. This gives an estimate of $\tilde{p}_x(t_{ij} = t, t_s = t_0)$. We repeat the procedure until the average of the estimated $\tilde{p}_x(t_{ij} = t, t_s = t_0)$ stabilizes.

Table C.1: Distribution of Education in the U.S., 1980 and 2007

1980

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates	Single	Marginal distribution
No high school degree	7.6	3.2	0.9	0.2	6.2	18.2
High school graduates	5.2	13.0	5.3	3.3	8.2	35.0
Some college	0.8	2.5	3.8	4.2	4.4	15.6
College graduates	0.2	0.9	1.5	6.6	3.7	12.9
Single	4.6	5.5	3.9	4.3	0	18.3
Marginal distribution	18.4	25.1	15.4	18.5	22.5	

2007

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates	Single	Marginal distribution
No high school degree	2.2	1.1	0.3	0.1	2.8	6.5
High school graduates	1.4	7.3	2.8	1.6	8.3	21.4
Some college	0.6	3.5	5.6	3.3	8.4	21.3
College graduates	0.2	1.8	3.2	11.3	7.6	24.0
Single	3.5	10.0	7.0	6.3	0	26.8
Marginal distribution	7.8	23.6	18.8	22.7	27.1	

Table C.2: Sorting Parameters in the U.S., 1980 and 2007

1980

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates	Single
No high school degree	2.28	0.70	0.32	0.07	1.52
High school graduates	0.81	1.48	0.98	0.50	1.04
Some college	0.26	0.64	1.58	1.44	1.25
College graduates	0.07	0.29	0.75	2.76	1.28
Single	1.37	1.19	1.40	1.26	0

2007

Wives' Education \ Husbands' Education	No high school degree	High school graduates	Some college	College graduates	Single
No high school degree	4.34	0.69	0.26	0.08	1.59
High school graduates	0.82	1.44	0.69	0.34	1.43
Some college	0.34	0.69	1.39	0.68	1.45
College graduates	0.10	0.31	0.70	2.07	1.17
Single	1.67	1.58	1.38	1.04	0