Marital Sorting and Inequality: How Educational Categorization Matters*

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Abstract

We use detailed data from Danish education registers to revisit the link between education-based marriage market sorting and income inequality. Our main contribution is a novel categorization based on "educational ambition", which takes into account starting wages and wage growth trajectories of graduates to unmask heterogeneous returns within tertiary education. We compare these educational-ambition types to common categorizations based on the level of education (primary, secondary, tertiary) and the field of study. First, we find an increasing trend in sorting by educational ambition while trends are flat for the common categorizations. Second, we scrutinize the role of changing marginal distributions for this result. Third, we study various counterfactual scenarios in a decomposition analysis and find that conclusions about contributing factors to rising income inequality also depend on the mapping between education and marriage market types. While increasing sorting based on the level of education has not contributed to increasing income inequality in Denmark over the last 40 years, increasing sorting based on ambitious, i.e., high return educational programs has amplified the trend.

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1 Introduction

Increasing income inequality has been documented for a wide set of developed countries over the last several decades (Chancel et al., 2022). On top of this increase, there is an abundance of correlational evidence for homophily in marriage markets, i.e., the tendency that individuals marry their likes in terms of, e.g., age, education, physical attractiveness, or wealth (Chiappori et al., 2012; Lee and McKinnish, 2018; Fagereng et al., 2022). Increasing sorting in marriage markets along these dimensions might amplify trends in inequality. This mechanism has received a lot of attention in the literature (Kremer, 1997; Fernández and Rogerson, 2001; Greenwood et al., 2014, 2016; Hryshko et al., 2017; Eika et al., 2019). Because income increases in education, the question is whether more education-based sorting leads to increasing income differences between households.

Existing studies typically rely on a specific education-based categorization, e.g., non-college and college (Greenwood et al., 2016) or primary, secondary, and tertiary (short and long) education (Eika et al., 2019). Moreover, each study uses a specific measures of sorting (e.g., correlations, distances, or measures based on the contingency table). Different categorizations and sorting measures make the results of these studies hard to compare. Against this background, the purpose of our paper is threefold. First, we show that the sorting measure and the educational categorization are not innocuous choices. Second, we scrutinize how changing marginal distributions of education affect a prominent class of frequency-based sorting measures. Third, we propose a new education-based categorization based on labor market outcomes and show that it yields an improved understanding of the effect of marital sorting on inequality.

We start out by showing that how one categorizes individuals based on their educational attainment, e.g., by the level, length, or field of education, matters. The reason is that the top educational category, i.e., university graduates, masks a lot of income heterogeneity (Breen and Salazar, 2011; Eika et al., 2019). Consequently, we develop a novel education-based categorization of marriage-market types that takes this income heterogeneity into account. We base it on the labor market outcomes that educational programs are associated with. To this end, we merge detailed Danish education registers with the labor market histories of all program graduates and compute continuous starting wages and wage growth trajectories at the level of the educational program. We group individuals based on their similarity in these two dimensions using the k-means algorithm and interpret individual who graduate from educational programs associated with high starting wages and high wage growth as *ambitious* with respect to their career. Therefore, we label our categories *educational-ambition* types.

We compare our educational-ambition types to common educational categorizations to assess how they affect conclusions about trends in education-based sorting. Based on a weighted sum of likelihood indices, a well-known frequency-based measure of sorting (Eika et al., 2019; Chiappori et al., 2020b), we find that conclusions about the degree and trend of education-based sorting differ significantly across categorizations. Using common categorizations such as the level of education or field of study, the time profiles of sorting are mostly flat in Denmark over the last 40 years, consistent with what Eika et al. (2019) find for the US.In contrast, marital sorting based in educational ambition exhibits a markedly increasing trends, i.e. "power-couples" are more likely to form now than previously.

We motivate the link between educational ambition and choices in the marriage market with the idea that the educational program an individual graduates from acts as a signal in the marriage market. This has been shown by Wiswall and Zafar (2021). The signal contains relevant information because the flip side of high wage growth is often a high level of working hours and limited flexibility (Goldin, 2014) or lower expected fertility (Jones et al., 2008).[1] Thus, the educational-ambition type of a (potential) spouse can be thought of as a predictor for expected future time inputs to home production and, specifically, childcare. We argue that educational ambition affects marriage formation through this channel.

Finally, using our novel educational-ambition categorization, we revisit the question to what extent increasing inequality is driven by increasing education-based marriage market sorting. Greenwood et al. (2016) find that changing marital decisions account for about 20% of the rise in income inequality in the US between 1960 and 2005 (holding educational choices fixed). Consistently, Eika et al. (2019) argue that increasing returns to education, not marital sorting, are the primary source of increasing inequality. The reason is that increased education-based sorting primarily reflects shifting marginal distributions and its contribution to growing inequality is thus limited (see also Breen and Salazar, 2011; Breen and Andersen, 2012; Chiappori et al., 2020a). In contrast, we find that the contribution of educational-ambition sorting to income inequality has been growing over time. Based on a distributional decomposition method inspired by Eika et al. (2019), DiNardo et al. (1996), and Fortin et al. (2011), we find that increased sorting by educational ambition can explain a substantial part of the increasing inequality in Denmark, although the major part is explained by increasing returns to ambitious educational programs. Moreover, we show that increased selection into ambitious educational programs has amplified the increasing inequality in the upper half of the income distribution.

[1] Although cross-sectional correlations between income and fertility have been negative historically, this relationship has recently weakened or even reversed in advanced economies (Doepke et al., 2022).

The remainder of the paper is organized as follows: Section 2 introduces our data and the strategies we use to measure education-based types and marital sorting. Section 3 discusses differences between common educational categories and educational-ambition types and how these differences influence the measurement of marital sorting. Section 4 presents the counterfactual analysis. Section 5 concludes.

2 Measurement

2.1 Data

We use Danish register data provided by Statistics Denmark for our analysis. Our data contains detailed yearly observations for all residents between 1980 and 2018. Unique person IDs identify individuals across registers. The data cover demographic variables, the person ID of the (married or cohabiting) partner, education variables, earnings, wages, and labor market experience. We include both legally married and cohabiting opposite-sex couples in the analysis and, for brevity, refer to both types of couples as married in the remainder of the paper.[2] We use population-wide registers to find all residents in Denmark in the age range 19–60 in the years 1980-2018. This corresponds to an average of 3,031,511 individuals per year. The population of couples with both partners in the age range 19–60 consists of 1,800,866 individuals per year on average. There is an upward (downward) trend in cohabitation (legal marriage), but the combined stock of couples is relatively stable over time.[3] We calculate yearly household income by adding the labor income of spouses, which includes both wages and income from self-employment.[4]

2.2 Measuring Sorting

From an empirical perspective, positive assortative matching (PAM) manifests itself as a positive association of spousal types in the cross section. This association can be measured based on correlation coefficients, distance measures, or the frequency distribution of couples' types (see, e.g., Fernández and Rogerson, 2001; Greenwood et al., 2014, 2016; Abbott et al., 2019). Determining whether sorting changes over time has proven elusive because the marginal distributions

[2]While cohabitation is not a legal status per se, couples who are judged to be cohabiting (samlevende) enjoy some of the same status as married couples. Cohabiting couples are identified based on a number of criteria: two opposite-sex individuals who have a joint child and/or share the same address, exhibit an age difference of less than 15 years, have no family relationship, and do not share their accommodation with other adults.

[3]Figure A.1a in the Appendix depicts the evolution of the stocks of different couple types and their age composition during our period of interest.

[4]Specifically, we use the variables $ERHVERVSINDK\_13$ from the income register IND.

of types in the marriage market change as well. We follow Eika et al. (2019) and Chiappori et al. (2020b, 2021) who focus on the frequency-based approach. A benefit is that this approach allows us to take changing marginal distributions into account flexibly and transparently by constructing weights for couples with different type combinations. These weights can be used to construct aggregate sorting measures that are comparable over time. We analyze below how alternative weighting schemes affect results about trends in marriage market sorting, and find that the choice of weights is important.

We first define the sorting measure for different couple types. Assume every couple i consist of two individuals, (i, m) and (i, f), where m and f indexes males and females. Each individual has a one-dimensional type t. Let the type, t, be a categorical variable with $t \in \{1, \ldots, j, \ldots, N\}$, where N is the number of categories. For example, these categories may represent levels of education (primary, secondary, tertiary, i.e., $N = 3$). For each category, the sorting measure is a likelihood index that relates the observed frequency of couples to the expected frequency under random matching (the denominator), which is given by the product of the marginals:

$$s(j, j') = \frac{P(t_{i,m} = j, t_{i,f} = j')}{P(t_{i,m} = j) P(t_{i,f} = j')}. \tag{1}$$

By summing across the categories in which the male and female types are identical, we get the aggregate sorting measure

$$\mathcal{S} = s(1,1) \times w_1 + s(2,2) \times w_2 + \cdots + s(N,N) \times w_N, \tag{2}$$

where $\{w_1 \ldots w_N\}$ are the weights for the respective categories. As discussed by Chiappori et al. (2020b), these weights can be thought of as a convex combination of the male and female marginal distributions:

$$w_j = \lambda P(t_{i,m} = j) + (1 - \lambda) P(t_{i,f} = j), \tag{3}$$

where the first (second) term is the contribution of the male (female) marginal distribution to the weight and λ is in the unit interval.

We compare this to the weighting schemes used in other papers. Greenwood et al. (2014, 2016) are not explicit about weighting. They consider two educational categories (college, non-college) and, i.a., a sorting measure that is based on the frequency distribution of type-combinations among married couples. The authors divide the sum of the diagonal elements (trace) of the matrix formed by the contingency table by the trace of the counterfactual matrix that would arise under random matching in the two years. A ratio above one is indicative of PAM. Greenwood et al. (2016) argue that PAM has increased over time because the ratio increased from 1.08 in 1960 to 1.43 in 2005 in US data.[5] The random matching counterfactual in the denominator takes changing marginal distributions into account, and, in fact, the trace-based sorting measure is mathematically equivalent to the weighted measure used in Eika et al. (2019). We shows this in Appendix B.

Eika et al. (2019) highlight the importance of weighting to make the comparison of sorting measures for different years meaningful. To calculate the aggregate sorting measure, they combine (1) and (2) with weights that are computed along the diagonal of the contingency table under random matching:[6]

$$w_j = \frac{P\left(t_{i,m} = j\right) P\left(t_{i,f} = j\right)}{\sum_{j=1}^{N} P\left(t_{i,m} = j\right) P\left(t_{i,f} = j\right)}. \tag{4}$$

An advantage of the Eika et al. (2019) weights is that they are solely based on the marginals and not on the realized sorting patterns along the diagonal.[7] Nevertheless, compared to the general weights discussed in Chiappori et al. (2020b), equation 3, the Eika et al. (2019) weights are not free of assumptions as they impose random matching. They are also not in general consistent with (3). They coincide with a convex combination of the marginals if the distribution of males and females across types is uniform. In that case, λ does not matter. If this distribution is non-uniform for either males or females, as in the data, the Eika et al. (2019) weights lie outside the range determined by (4). However, the weight according to (3) approaches the weights in (4) as λ moves towards the more unequal side of the market. We discuss this in more detail in Appendix B and explore how the different weighting schemes affect trends in the aggregate sorting measure in Section 3.

2.3 Defining Educational Categories

We use four-digit educational program codes (ISCED) that uniquely identify all educational programs in Denmark. We consider three common categorizations of individual educational attainment. First, the highest level of completed education, i.e., primary (compulsory schooling), secondary (vocational degrees), and tertiary (higher) education (three categories). Second, we

[5] See Table 1 in Greenwood et al. (2016).

[6] Note that male and female types j are identical along the diagonal, so in contrast to (1), we do not need to distinguish the male and female types by j and j'.

[7] An alternative that we test below is to instead use the observed frequencies of couple types along the diagonal, e.g., $w_j = \frac{P(t_{i,m}=j, t_{i,f}=j)}{\sum_{j=1}^{N} P(t_{i,m}=j, t_{i,f}=j)}$.

take the length of educational programs into account by dividing the tertiary education category into two subcategories: Bachelor degree programs (four years or less, vocational colleges and universities) and Master/PhD programs (five years or more, graduate-level education at universities). This results in four categories. Third, we subdivide the tertiary education category into six fields of study: (i) social and health; (ii) teaching; (iii) business, admin, and law; (iv) social sciences; (v) engineering, natural sciences, and technology; (vi) humanities.

Our novel educational-ambition categorization is also based on educational attainment, but groups programs based on the associated labor market outcomes of individuals who graduate from them. For each educational program in Denmark in the last 40 years, we measure two outcomes: starting wage, w_0, and wage growth, g. To compute these, we use all individuals in the data who completed their education after 1980.[8] Throughout, we use hourly wages to abstract from the intensive margin. We deflate hourly wages by regressing wages on year effects with 2000 as the base year. The starting wage w_0 is the average hourly wage of individuals during the first five years in the labor force.[9] To calculate the average growth rate g, we measure the percentage change between w_0 and w_1 where w_1 is the average hourly wage of individuals in years 9–11 in the labor force.[10] We average over multiple years for both w_0 and w_1 to smooth out year to year variation that is unrelated to worker productivity. The (expected) wage growth associated with an educational program is thus the percentage change between w_0 and w_1, averaged over all graduates in the sample. To cluster individuals based on starting wage and growth, we use the k-means algorithm.[11] The method minimizes the within-cluster variation in the two dimensions and, thus, produces relatively homogeneous groups in terms of starting wages and growth.

[8]That is, expected wage growth g_i of an individual who enters in 1990 is based on the observed wage growth trajectories of all that enter the educational program later and prior, e.g., in 1980 and 2005. We could have chosen to only use individuals that already graduated or only graduated around the time of starting the education. However, this would imply less individuals in the group. Which of the two strategies is best depend on where the uncertainly lies. If we assume that individuals have perfect knowledge about the labor market trajectories of a given educational program and that programs are stable over time then including individuals graduating in the future is optimal, since it reduces the noise in the estimate of average starting wage and wage growth.

[9]We define labor market entry as the year in which individuals complete the highest education obtained before turning 35 if observed or the highest education observed at the oldest age if not turning 35 before 2018.

[10]The focus on early career wage profiles is motivated by studies finding that wage profiles stabilize later in one's career (Bhuller et al., 2017).

[11]For an overview, see Steinley (2006).

3 Results

We start out by comparing two classifications of educational programs in terms of starting wages and wage growth in Figure 1. First, a standard classification based on the level of education in four categories: primary, secondary , shorter tertiary (Bachelor), and longer tertiary (Master & PhD)), see Panels (a) and (c). Second, the educational-ambition classification that groups educational programs into four k-means clusters using starting wages and wage growth, see Panels (b) and (d).[12] The upper two Panels locate all programs in the space of standardized starting wages and wage growth rates. The first important observation is the vast heterogeneity in both dimensions, which the educational-level classification hardly takes into account. In Panel (a), one can discern a ranking in terms of starting wages, which are on average low for compulsory schooling (blue squares) and high for long tertiary education (large gray diamonds). But the overlap is vast. For example, many secondary (red circles) and short tertiary (small orange diamonds) programs have higher starting wages than longer tertiary programs. In the growth dimension, there is no clear pattern.

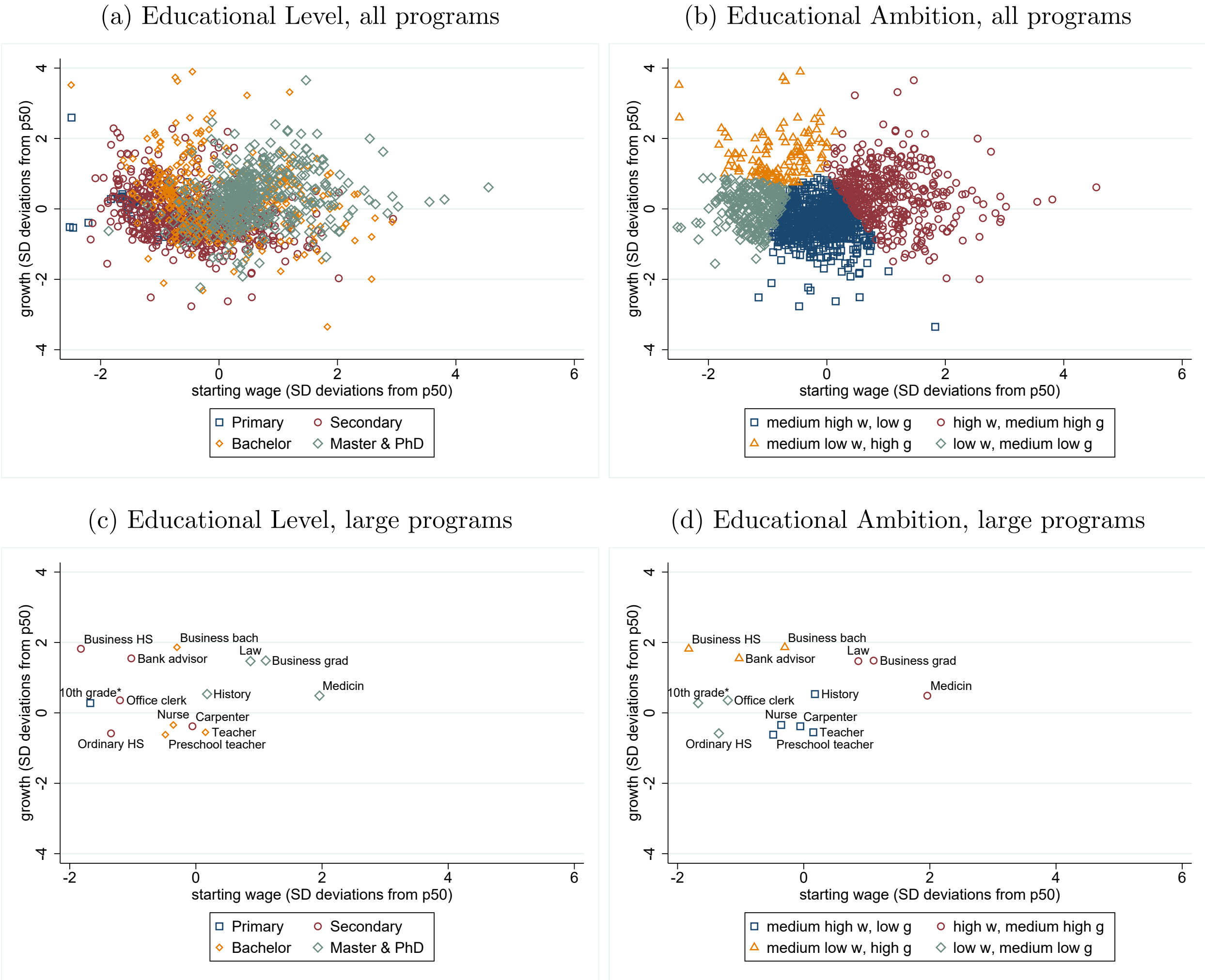
Panel (b) shows how the k-means algorithm partitions the educational programs into four categories based on starting wages and growth. By construction, these clusters are internally more homogeneous in said dimensions than the standard categories. Here, the red category (circles) includes the highest starting wages. Tertiary programs with low starting wages are not part of this cluster. The dispersion of wage growth within this cluster is relatively large, it ranges from -2 to 4 standard deviations relative to the median. The blue category (squares) includes starting wages within roughly $\pm$ 1 standard deviations from the median. It is clearly delimited from above and does not include programs with high wage growth. The orange category (triangles) has relatively low starting wages but some programs with the highest wage growth overall. Finally, the gray category (diamonds) has the lowest starting wages and wage growth is delimited within $\pm$ 1 standard deviations.

Panels (c) and (d) zoom in on 14 exemplary educational programs with a large number of graduates.[13] In total, these program constitute 21% of all graduates. Three of the 5-year tertiary programs included—law, business, and medicine—end up in the educational-ambition category with very high starting wages and relatively high wage growth. The fourth 5-year tertiary program included—history—is, however, part of the blue cluster with medium-starting wages and low wage growth. Thus, the k-means algorithm combines history with

[12] Results for additional classifications are depicted in Figure A.3 in the Appendix.

[13] These are 3-4 largest four-digit educational programs in 2018. History is a relatively small program that we include to illustrate heterogeneity within tertiary education.

Figure 1: Starting wages and growth of educational programs by type



Source: The population of couples see section 2
Note: Each point in the figures represents the average wage growth and starting wages in educational programs with at least ten graduates, panels (a) and (b), observed by 2018. In panels (c) and (d) we show 14 exemplary programs with many graduates. The symbols of points refer to the educational level or educational-ambition type associated with the program. Axes are deviations measured in standard deviations from the median. * We split primary education (9th/10th grade) into five groups based on the geographical region of graduation.

programs that are similar in terms of labor market outcomes but separate according to the program length categorization, e.g., (preschool) teachers, nurses, and carpenters. Teachers and nurses graduate from Bachelor degree programs while carpenters have a secondary, vocational degree. Similarly, individuals who finished compulsory schooling, high school, or a vocational degree as office clerks, are grouped together in the educational-ambition categorization (due to comparable starting wages) but are separated in the educational-length classification. Finally, three programs with relatively low starting wages but high growth—degrees from high schools that specialize in business, bank advisors, and short tertiary degrees in business—are also in the same educational-ambition category but separate in terms of educational level.

Table 1 shows a cross-tabulation of educational ambition and educational length. The char-

Table 1: Cross-Tabulation of Educational Level and Educational Ambition

	Educational-ambition				
Educational length	(i)	(ii)	(iii)	(iv)	Total
Primary	0.97	0.06	0.04	26.93	28.01
Secondary	21.79	2.22	4.81	21.05	49.87
Bachelor	9.60	3.32	0.56	1.66	15.14
Master & PhD	1.34	5.48	0.06	0.10	6.98
Total	33.70	11.09	5.47	49.75	100.00

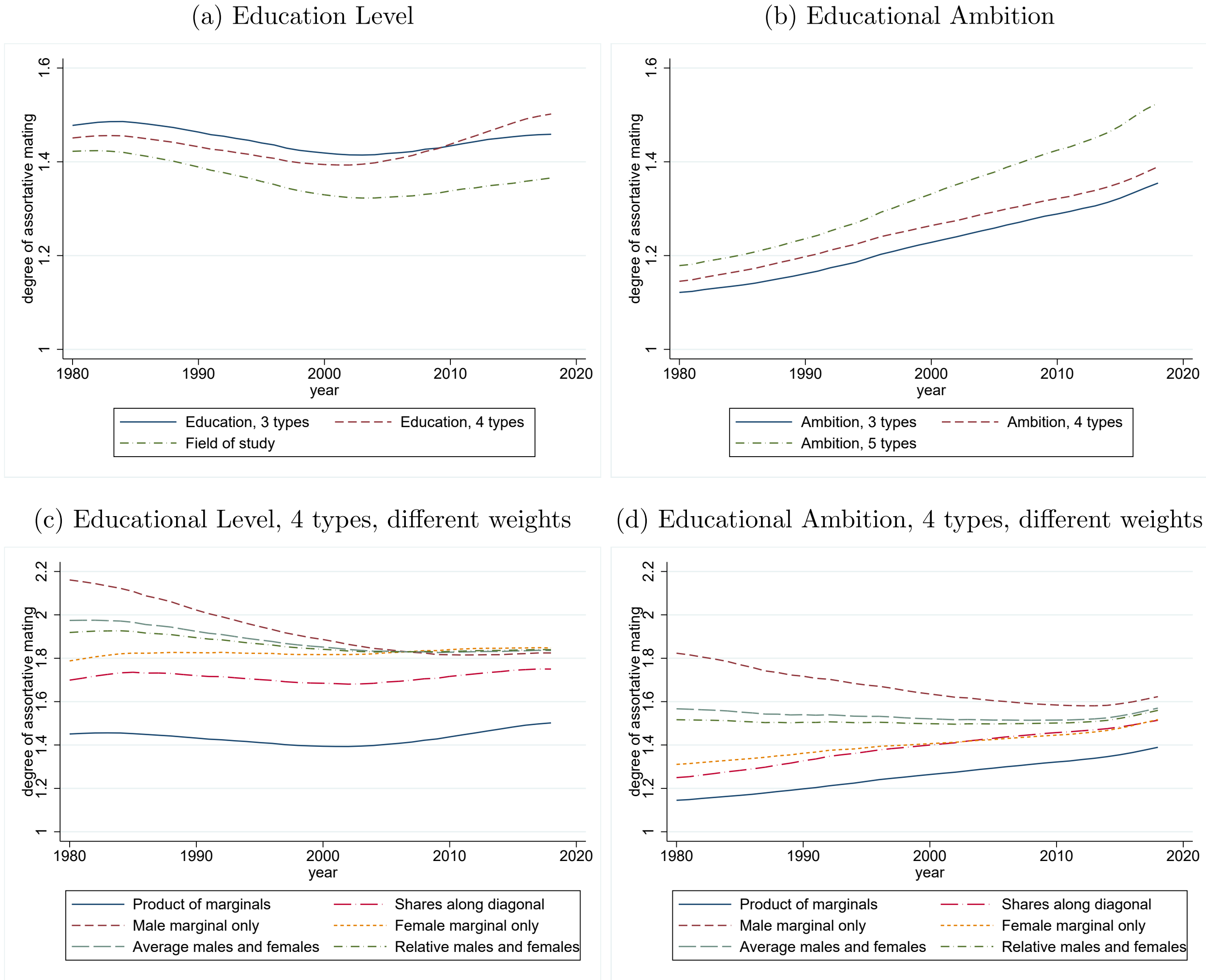
acteristics of the four educational-ambition categories and their relation to standard categories can be summarized as follows: i) medium-high starting wages and low growth (blue squares) comprising around 33% of the population with mostly secondary but also Bachelor degrees (e.g., nurses, teachers, and carpenters); ii) high starting wages and medium-high growth (red circles) comprising around 11% of the population with mostly long tertiary but also some secondary degrees (e.g., graduate degrees in business, law, and medicine as well as vocational degrees related to information technology); iii) medium-low starting wages and high growth (orange triangles) comprising around 6% of the population with mostly secondary education (e.g., business high school and bank advisors); iv) low starting wages and medium-low growth (gray diamonds) comprising around 50% of the population with mostly primary but also secondary degrees (e.g., compulsory schooling, high school graduates, office clerks). While category (ii) could be interpreted as the top group, no clear ranking emerges among the other three.

Figure 2 explores differences between educational-level categories (Panel (a)) and educational-ambition types (Panel (b)) in terms of the aggregate sorting measure $\mathcal{S}$ defined in Equation (2). For both categorizations, we include results for multiple numbers of groups N.[14] The figure also shows results for different weighting schemes, that is, different ways of accounting for changes of the marginal distributions over time, for both types of categorization (Panels (c) and (d)). Consistent with Eika et al. (2019) for the US, Panel (a) shows that the weighted sum of likelihood indices does not increase after 1980 for the standard categorizations.[15] However, based on the educational-ambition categorization, we see a steady increase in sorting. These results hold for all numbers of groups. Below, we explore the implications of increasing educational-ambition-based sorting for the link between marriage market sorting and income inequality.

[14]Standard: three (level) and four (length) educational types, as well as the classification that subdivides tertiary education by field of study. Educational-ambition: 3, 4, and 5 clusters.

[15]Our results for Education, 3 types (level) in Figure 2 Panel (a) are consistent with the results reported for Denmark in Eika et al. (2019). In particular our Figure A.4 Panel (a) and their Figure 9 Panel (a).

Figure 2: Aggregate Sorting Measures



Source: The population of couples, see Section 2.
Note: Panels (a) and (b) report aggregated sorting $\mathcal{S}$ (equation (2)) by various standard educational types and educational-ambition types from 1980–2018 using the weights from Eika et al. (2019) defined in equation (4). The disaggregated likelihood indices can be found in Figure A.4. Panels (c) and (d) report $\mathcal{S}$ using weights according to Equation (4) ("Product of marginals", blue). The "Shares along diagonal" weights use the observed contingency table (red, dash-dots, see Section 2.2). The remaining weights are defined by Equation (3) for different values of λ. For male marginal only $\lambda = 1$, female marginal only $\lambda = 0$, average males and females $\lambda = 0.5$, and relative males and females $\lambda \approx 0.375$.

Panels (c) and (d) of Figure 2 illuminate the role that the weights play for these conclusions. Evidently, the weighing scheme affects conclusions about trends in sorting, specifically for the educational-ambition classification. The results in Panels (a) and (b) use the weighting of Eika et al. (2019). That is, the blue solid line in Panel (c) corresponds to the red dashed line for four educational types in Panel (a). Similarly, the blue solid line in Panel (d) corresponds to the red dashed line for four educational-ambition types in Panel (b). We find in Panels (c) and (d) that the weights used in Panels (a) and (b) based on Eika et al. (2019) most closely correspond to a weighting that puts all the emphasis on changes to the marginal type distribution of females. Referring back to the definition of weights in Equation (3), this means that the implied λ must be relatively close to zero.

To understand why diagonal weights implicitly put the weight on the marginal distribution of female types, consider that historically the educational attainment of women lagged behind men but caught up over the last couple of decades (Goldin, 2006). If there are more educated men than educated females, and educated men have a preference to marry their like, some of them have to stay single or marry down because highly educated women are in short supply. Figure A.2 in the Appendix shows the development of the marginal distributions for Denmark since 1980. The share of men with long-cycle tertiary education has more than tripled between 1980 and 2018. But for women, this share has increased by factor of 13. Similarly, for our educational-ambition types, the share of men with high starting wages and high wage growth has almost doubled, while there are nearly eight times as many highly ambitious women in 2018 compared to 1980. If high-type women are relatively scarce, it is reasonable to expect that an increase in their supply will have a big impact on the allocation in the marriage market. A constraint on marriage market matching is relaxed and, hence, more sorting occurs. For this reason, it is unsurprising that the weights based on the product of the marginals (Eika et al., 2019) correspond closely to the case in which all weight lies on the marginal distribution of female types. Other weights, e.g., the average of the male and female marginal distributions ($\lambda = 0.5$) or the ratio of the male changes in the marginal distribution to the total change for male and female marginal distributions ($\lambda \approx 0.375$) imply a relatively flat sorting trend also for the educational-ambition types. However, for all weightings, an increase occurs for educational-ambition types after 2013, while sorting by educational types remains flat.[16]

In sum, we find that the number of categories (N), merely shifts the level of the sorting measure and does not affect the trend. However, both the classification (standard educational or educational-ambition) and the weighting scheme matter for conclusions about trends in marital sorting. In the next section, we show that these differences also matter for conclusions about the link between marital sorting and inequality.

4 Counterfactual Analysis

We rely on the counterfactual re-weighting method introduced by DiNardo et al. (1996) and follow the implementation of Eika et al. (2019). Our goal is to show how sensitive conclusions about the influence of marriage market sorting on trends in income inequality across households are to the alternative categorizations of the marriage-market types that we have discussed.

Specifically, we analyze counterfactual household-level income inequality in 2018 under four

[16] Figure A.5 in the Appendix shows how all six weights change over time.

different scenarios: (i) couples match randomly in the marriage market; (ii) couples match according to matching probabilities fixed in 1980; (iii) couples have their return to educational (either by educational level or educational ambition) fixed at the 1980 level; (iv) the marginal distributions of education (either by educational level or educational ambition) are fixed at the 1980 level.

We construct (i) with a rematching algorithm. First, the rematching algorithm treats all married 2018 individuals as singles. Second, it draws potential couples by sampling males and females according to the respective marginal distributions. Third, it is decided by a draw from a binomial distribution with $p = 0.5$, due to the random matching scenario, if the potential couple becomes a household in this counterfactual setting. Finally, all the remaining non-matched individuals are treated as singles and the process is repeated. The rematching algorithm stops when all individuals have been assigned to a counterfactual household.

Scenario (ii) is constructed similarly to (i). The only difference is that we use different matching probabilities, p. These probabilities correspond to the matching probabilities implied by the 1980 allocation of couple types. For each possible couple combination of $(t_{i,m} = j, t_{i,f} = j')$, we get the implied 1980 matching probability by taking the average between the conditional probability that a male (female) of type $t_{i,m} = j$ $(t_{i,f} = j)$ is matched with a female (male) of type $t_{i,f} = j'$ $(t_{i,m} = j')$ based on the observed likelihood indices, cf. Equation (1).

To analyze the counterfactual income inequality under scenario (iii), we use a household re-weighting factor, $\widehat{\psi_y}$, to construct the counterfactual household income distribution, where y denotes household income, x couple combination of $(t_{i,m} = j, t_{i,f} = j')$, s matching probabilities, and τ time:

$$\widehat{F}(y|\tau_y = 1980, \tau_x = 2018, \tau_s = 2018) = \int F_{Y|X}(y|x, \tau_y = 1980)\psi_y dF(x|\tau_x = 1980), \tag{5}$$

with

$$\widehat{\psi_y} = \frac{P(\tau_x = 2018|x, \tau_s = 2018)}{P(\tau_x = 1980|x, \tau_s = 2018)} \frac{P(\tau_x = 1980)}{P(\tau_x = 2018)}. \tag{6}$$

We obtain $\widehat{\psi_y}$ by following the approach suggested by Fortin et al. (2011). To get the conditional probability of being in 1980 for couple combination x under the matching probabilities at $\tau_s = 2018$, we use the rematching algorithm on 1980 households with implied 2018 probabilities. Intuitively, couple combinations x which are relatively more present in 2018 are weighted greater than one in the counterfactual income distribution and vice versa.

We obtain the last scenario (iv) with a similar approach as for (iii) by re-weighting households in the 2018 income distribution relative to changes in the marginal distributions of $t_{i,m}$ and $t_{i,f}$. In this case the re-weighting factor is $\widehat{\psi_x} = (\widehat{\psi_y})^{-1}$.

Importantly, these counterfactual results rest on an independence assumption between matching probabilities s, the income distribution y, and marginal distributions of $t_{i,m}$ and $t_{i,f}$. For example, we assume that changing matching probabilities in the marriage market do not change returns to types or the selection into educational level or educational ambition. In this sense, the exercise is similar to a standard extended Oxcaca-Blinder decomposition, where we can change one set of parameters at a time.

We summarize the counterfactual household-level income inequality in 2018 under the four different scenarios in Table 2. Income inequality is reported by both the Gini coefficient which summarizes inequality in the entire distribution, the P90 to P50 ratio reflecting the inequality in the upper half of the income distribution, and the P50 to P10 ratio reflecting inequality in the lower half of the income distribution. In the first row, we present the results using the real data. As a first observation, we see that household-level income inequality for couples has increased from 1980 to 2018 both measured by the Gini coefficient (Panel (a)), the P90 to P50 ratio (Panel (b)), and the P50 to P10 ratio (Panel (c)). The true change of the respective inequality measure in the data is denoted as 100%, and we compare the arising inequality in the different counterfactual scenarios to this baseline.

The results for random matching (i) show that the level of income inequality is lower in 2018 if couples form with probabilities that resemble random matching, i.e., do not sort. This is in line with findings from the US (Eika et al., 2019) showing that sorting increases the *level* of household income inequality. However, the 1980 level of inequality implied random matching is not far from the truth. One explanation follows an argument in Greenwood et al. (2016): for higher marital sorting to impact inequality, the (more educated) wives must work.

Scenarios (ii)-(iv) decompose the increasing income inequality *trend*. Had the matching probabilities been kept fixed at the 1980 level as in scenario (ii), then the increase in inequality would have been less pronounced. In other words, changes in matching probabilities between 1980 and 2018 have amplified the increasing income inequality trend holding all other variables fixed. The impact of changing matching probabilities on the inequality trend is similar for the two classifications, educational level and educational-ambition types. The increase in inequality would have been 31% lower than the baseline for the educational level categorization and 29% lower for the educational-ambition categorization (Gini). The effect of holding matching probabilities fixed is larger at the lower half of the income distribution (P50/P10) compared to the upper half (P90/P50). Interestingly, our findings differ from others in the literature (Breen

Table 2: Counterfactual Changes in Income Inequality

	(a) Gini			(b) P90/P50			(c) P50/P10		
	1980	2018	Δ	1980	2018	Δ	1980	2018	Δ
Data	0.241	0.307	100%	1.52	1.69	100%	1.94	2.52	100%
(i) Random matching	0.239	0.281	–	1.54	1.64	–	1.92	2.09	–
(ii) Fixed matching prob.	1980	2018	Δ	1980	2018	Δ	1980	2018	Δ
Educational Level, 4 types	0.241	0.287	69%	1.52	1.67	86%	1.94	2.12	30%
Educational Ambition, 4 types	0.241	0.288	71%	1.52	1.67	91%	1.94	2.12	31%
(iii) Fixed returns to type	1980	2018	Δ	1980	2018	Δ	1980	2018	Δ
Educational Level, 4 types	0.241	0.251	15%	1.52	1.65	77%	1.94	1.88	-10%
Educational Ambition, 4 types	0.241	0.245	6%	1.52	1.59	41%	1.94	1.90	-8%
(iv) Fixed marginal dist.	1980	2018	Δ	1980	2018	Δ	1980	2018	Δ
Educational Level, 4 types	0.241	0.335	142%	1.52	1.72	119%	1.94	3.68	302%
Educational Ambition, 4 types	0.241	0.313	108%	1.52	1.64	70%	1.94	3.05	192%

Source: The population of couples see section 2
Note: Panel (a) reports the Gini coefficient, while panels (b) and (c) report the ratio of the 90th and 50th percentile and the ratio of the 50th and 10th percentile in the income distribution. We do this for 1980 and 2018 in the data and for four counterfactual scenarios using the re-weighting method introduced by DiNardo et al. (1996). For scenarios (ii)-(iv), we distinguish between categorizing educational programs by educational length or four educational-ambition types. Changes between 1980-2018 are denoted by Δ and scaled according to the change in the data being 100%.

and Salazar, 2011; Breen and Andersen, 2012; Eika et al., 2019; Chiappori et al., 2020a). We find that changing matching probabilities can explain a substantial part of the increasing trend in inequality in the Danish case. This indicates that sorting patterns are not only influenced mechanically by changing marginal distributions of $t_{i,m}$ and $t_{i,f}$ but also by changing preferences over partner types or changes to the matching process, e.g., reduced search frictions. Hence, we find that increased educational-ambition type sorting has contributed to the increasing household income inequality trend in Denmark between 1980–2018.

We confirm the conclusion made by Eika et al. (2019) that changes in returns to types (iii) explain a larger part of the increasing inequality than changing matching probabilities (ii). For the counterfactual Gini coefficients (or P50/P10 ratios) in 2018 when keeping returns to types fixed at their 1980 level, we see that Gini coefficients (or P50/P10 ratios) would barely have changed. This indicates that changes in returns to types have substantially amplified the increasing income inequality. The difference is less pronounced when looking at the P90/P50 ratios reflecting how changes in returns have mostly affected the difference between the top and bottom of the income distribution. Interestingly, the counterfactual P90/P50 ratio for educational-ambition types is lower than that of educational-level types. Thus, changing returns to educational-ambition types explains more of the increasing inequality in the upper half of the distribution. This might reflect heterogeneity in increasing returns to educational programs within tertiary education.

Finally, we find that conclusions about the impact of changing marginal distributions on increasing income inequality (iv) differs for the educational level and educational-ambition categorizations. In line with previous findings, we conclude that a shift in marginal educational distributions towards secondary and tertiary education has had a dampening effect on the inequality trend. The changes in the Gini coefficient, the P90/P50 ratio, and the P50/P10 would have been 42%, 19%, and 202% higher than the baseline, respectively, had the educational marginal distributions not changed since 1980. Interestingly, we reach the opposite conclusion for the P90/P50 ratio when fixing the marginal distributions of educational-ambition types in 1980. Hence, the shift towards higher starting-wage-and-growth educational-ambition types has amplified the increasing inequality in the upper half of the income distribution. This highlights the importance of disentangling heterogeneity within broad educational categories, especially for tertiary education, which includes educational programs that are associated with very different labor market outcomes.

5 Conclusion

During the last couple of decades, both household income inequality and the cross-sectional correlation of spousal attributes have increased. However, previous studies (Breen and Salazar, 2011; Breen and Andersen, 2012; Eika et al., 2019; Chiappori et al., 2020a) have shown that the effect of increased education-based sorting on inequality is limited because observing more couples in which both spouses have the same level of education primarily reflects shifting marginal distributions. These studies have in common that they rely on relatively coarse educational categories to measure sorting. In this paper, we argue that the categorization of types is not an innocuous choice when studying the link between sorting and inequality.

Using detailed Danish register data for legally married and cohabiting couples aged 19-60 for 1980-2018, we develop a novel education-based categorization of marriage-market types: educational-ambition types. These types are based on labor market outcomes of specific educational programs. We cluster programs by starting wages and early-career wage growth with the k-means algorithm.

We find that different educational categorizations affect conclusions about trends in education-based sorting. As for the US case (Eika et al., 2019), trends are mostly stable in the Danish case for this categorization. The educational-ambition types take heterogeneity within and across standard educational categories into account by, e.g., splitting high-starting-wage-and-growth tertiary programs (law, business, and medicine) and medium-starting-wage-and-low-growth tertiary programs (teachers, nurses, and preschool teachers) into different groups. The idea behind the educational-ambition categorization is that the educational program an individual graduates from is a signal in the marriage market. In contrast to standard educational categories, we see a steady increase in sorting, regardless of the number of categories (three, four, or five) based on the educational-ambition categorization.

We also contribute to the ongoing debate in the literature (Eika et al., 2019; Chiappori et al., 2020b) about how to use weights on the sum of likelihood indices in order to take changing marginal distributions into account when measuring aggregate marriage market sorting over time. We find that conclusions about sorting prior to 2013 depend on the specification of weights. After 2013, the conclusions about stable sorting by standard educational categories and increasing sorting by educational-ambition types are robust to different weightings. Based on this weighting exercise, we find indications that the rapid changes in the marginal educational-ambition type distribution for women towards high educational ambitions explain a substantial part of increased sorting.

Based on a counterfactual re-weighting exercise (DiNardo et al., 1996), we find that sorting increases the level of household income inequality in line with findings from the US (Eika et al., 2019). We further show how increased sorting by educational-ambition types can explain a substantial part of the increasing trend in inequality in the Danish case. This indicates that sorting is not only influenced mechanically by changing marginal distributions but also by changing preferences over partner types or changes to the matching process, e.g., reduced search frictions.

We confirm the conclusion made by Eika et al. (2019) that changes in returns to types explain a larger part of the increasing inequality than changing matching probabilities. Interestingly, changing returns to educational-ambition types explain more of the increasing inequality in the upper half of the income distribution compared to educational-level types. This might reflect heterogeneity in increasing returns to educational programs within tertiary education.

Finally, we find that conclusions about the impact of changing marginal distributions on increasing income inequality differ for the educational-level and educational-ambition categorizations. While a shift in marginal distributions towards secondary and tertiary education has had a dampening effect on the inequality trend, the shift towards higher starting-wage-and-growth educational-ambition types has amplified the increasing inequality in the upper half of the income distribution. We argue that this highlights the importance of disentangling heterogeneity within broad categories. This is especially important for tertiary education, which includes educational programs associated with very different labor market outcomes.

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Online Appendix

(not for publication)

A Data Appendix

Here provide all the details.

B Comparison of Sorting Measures and Weights

The weighted sum of likelihood indices used as an aggregate sorting measure in Eika et al. (2019) is equivalent to the trace-based measure of Greenwood et al. (2016). To see this, multiply the weight in equation 4 with the likelihood index in equation (1). The product of the two marginal distributions for the respective category cancels out and, assuming the simple case of two categories, one is left with the aggregate sorting measure

$$\mathcal{S} = \frac{P\left(t_{i,m} = 1, t_{i,f} = 1\right) + P\left(t_{i,m} = 2, t_{i,f} = 2\right)}{P\left(t_{i,m} = 1\right) P\left(t_{i,f} = 1\right) + P\left(t_{i,m} = 2\right) P\left(t_{i,f} = 2\right)}, \tag{A.1}$$

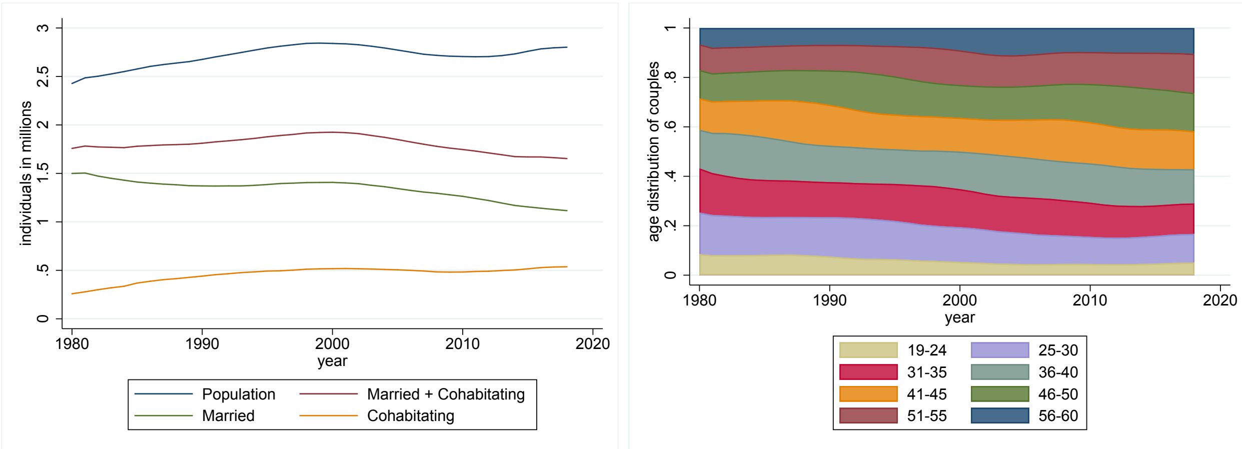
which is equivalent to the Greenwood et al. (2016) measure.

C Additional Results

Figure A.1: Marriage, Cohabitation, Age Composition

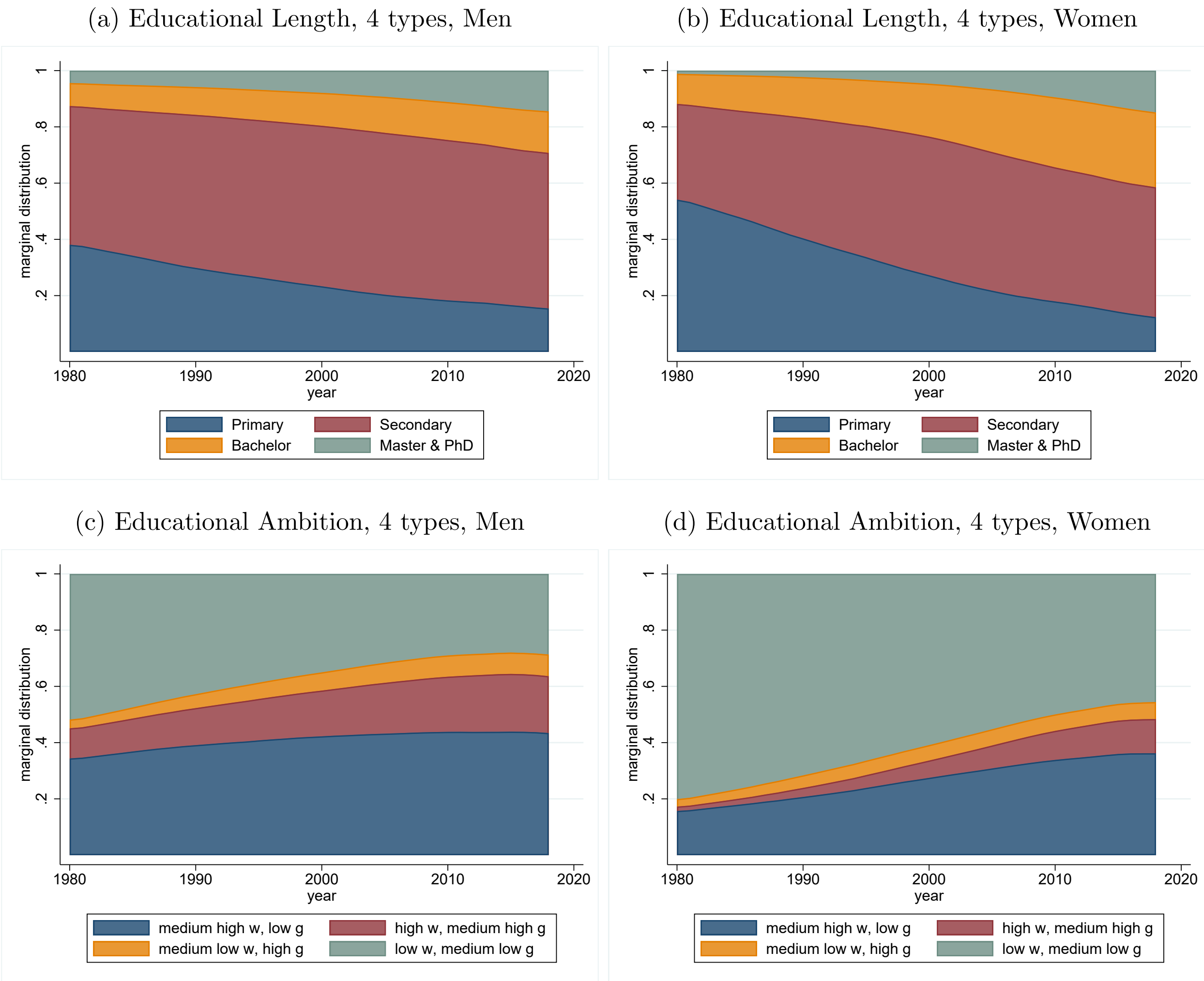
(a) Stocks of Couples

(b) Age Composition of Couples



Source: Panel a is based on the full population while panel b is based on the population of couples see section 2
Note: Panel a reports the development in numbers of individuals by marital status. Panel b plots the age distribution of individuals who are either legally married or cohabiting.

Figure A.2: Marginals

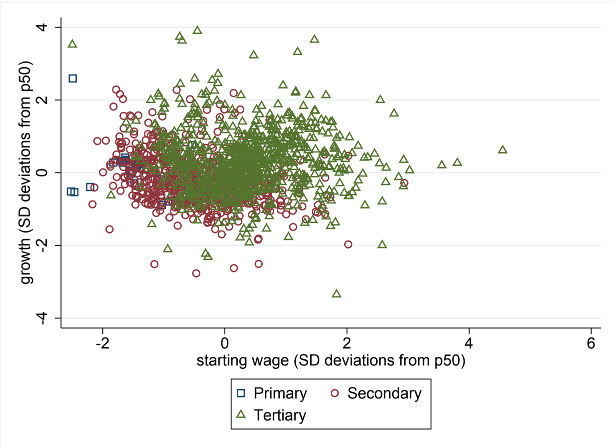


Source: The population of couples see section 2

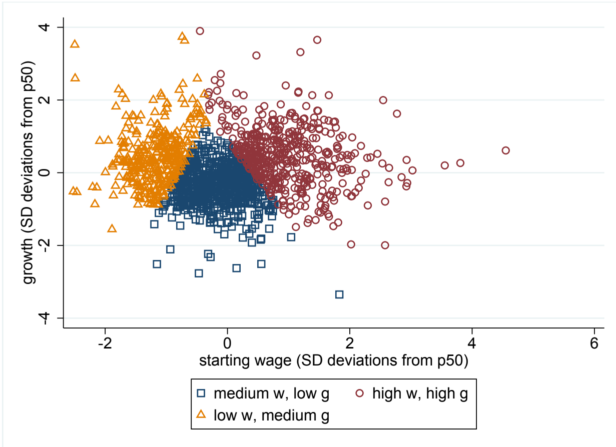
Note: Marginal distributions for men and women over time by educational length types or four educational-ambition types.

Figure A.3: Other classifications by starting wages and growth

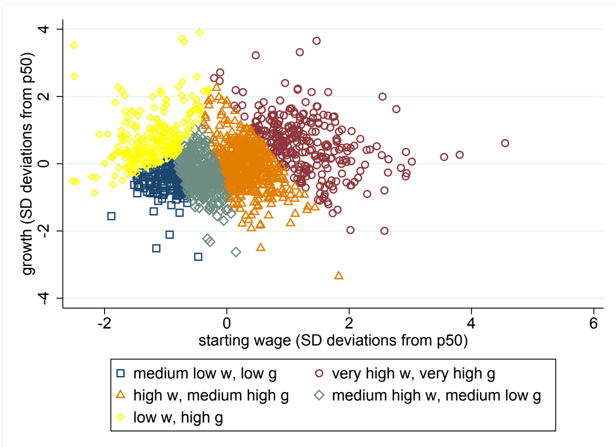
(a) Educational Level, 3 types



(b) Educational Ambition, 3 types



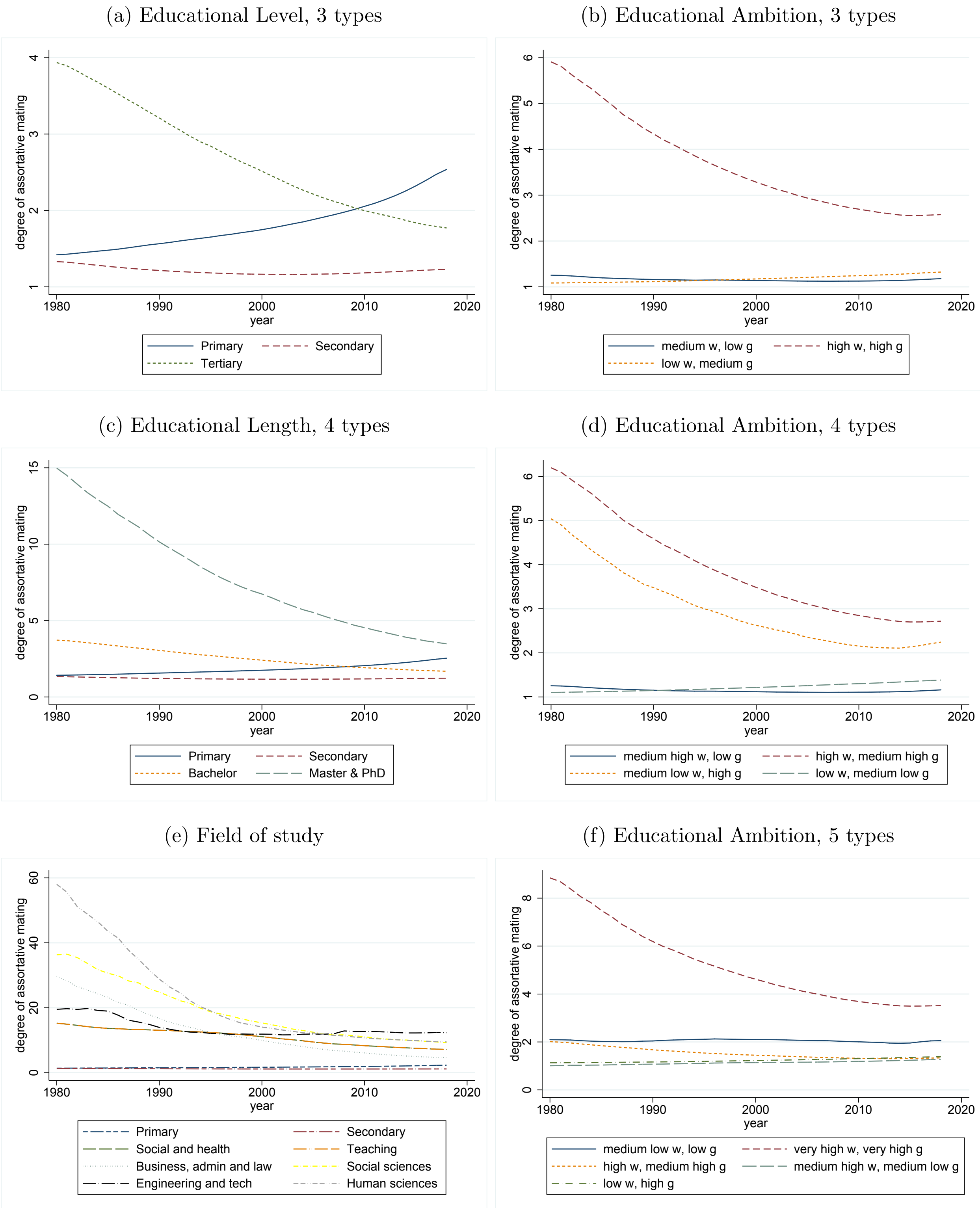
(c) Educational Ambition, 5 types



Source: The population of couples see section 2

Note: Each point in the figures represents the average wage growth and starting wages in educational programs with at least ten graduates observed by 2018. The symbols of points refer to the educational level or educational-ambition type associated with the program. Axes are deviations measured in standard deviations from the median.

Figure A.4: Disaggregated Sorting Measures

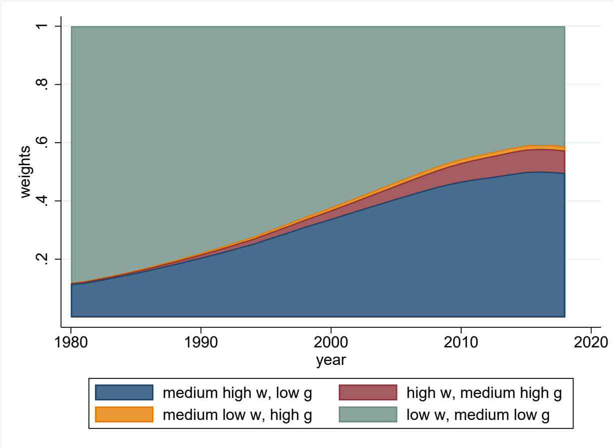


Source: The population of couples see section 2

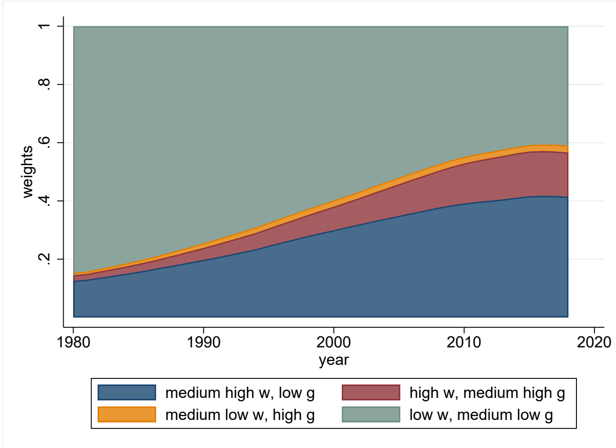
Note: Likelihood indices for assortatively matched couples cf. equation (1) for six different standard educational- and educational-ambition type categorizations.

Figure A.5: Weights for Educational Ambition, 4 types

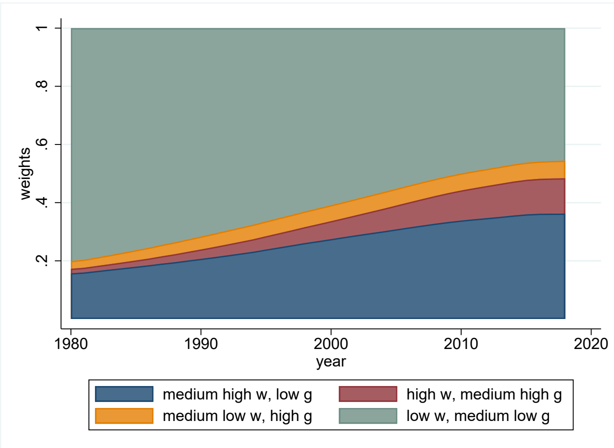
(a) Product of marginals



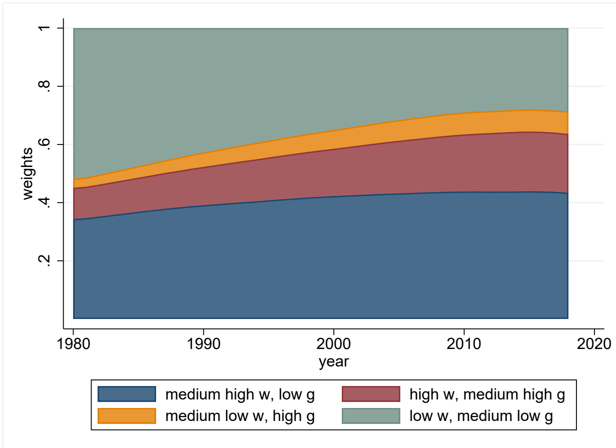
(b) Shares along the diagonal



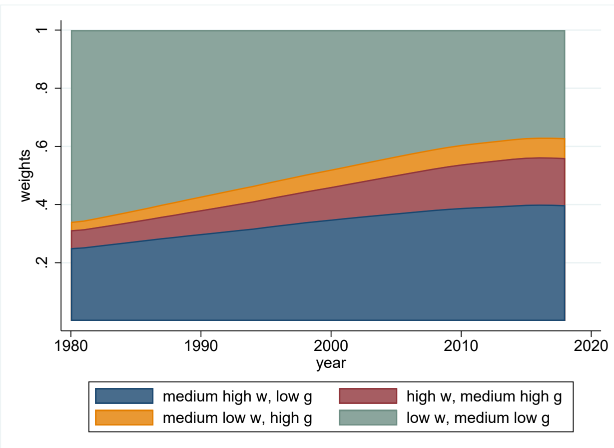
(c) Female marginal only



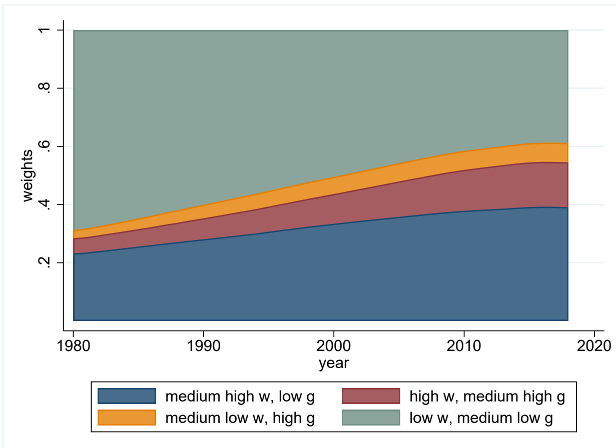
(d) Male marginal only



(e) Average males and females



(f) Relative males and females



Source: The population of couples see section 2
Note: Weights for assortatively matched couples cf. equation (4) for six different standard educational- and educational-ambition type categorizations.