Educational Ambition, Marital Sorting, and Inequality*

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September 9, 2025

Abstract

This paper revisits the link between education-based marriage market sorting and income inequality. Leveraging Danish administrative data, we develop a novel categorization of "ambition types" that is based on the labor market returns of detailed educational programs. In contrast to commonly-used education-based categorizations, we find a substantial increase in positive assortative matching by educational ambition over time. Moreover, changes in household composition by ambition explain more than 35% of increasing inequality since 1980. We conclude that the mapping from education to types matters crucially for conclusions about how education-based marriage market sorting contributes to rising income inequality.

*This paper is a substantially revised version of IZA DP No. 15912 (January 2023), which was circulated under the title "Marital Sorting and Inequality: How Educational Categorization Matters". First draft: October 2022. We thank the editor and two anonymous referees for detailed and constructive feedback. Discussions with Edoardo Ciscato, Rasmus Landersø, Elena Mattana, Laura Pilossoph, Jakob Søgaard, Basit Zafar, and audiences at Aarhus University, University of Copenhagen, Barcelona GSE, the DGPE network, DAEiNA, IAB Nuremberg, University of Michigan, Universidad de San Andres, SEHO 2024, SOLE 2024, Yale University, and the 2024 ASSA meetings have greatly improved the paper. Hans Magnus Appel Laursen provided excellent research assistance. Access to the Danish register data used in this study is provided by ECONAU, Aarhus University. Bastian Schulz thanks the Aarhus University Research Foundation (Grant no. AUFF-F-2018-7-6) and the Dale T. Mortensen Centre at the Department of Economics and Business Economics, Aarhus University, for financial support.

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1 Introduction

An ongoing debate questions the contribution of education-based positive assortative matching (PAM) in the marriage market to rising household income inequality. Some studies find evidence that assortative matching on education has strengthened in recent decades and argue that this has contributed to rising income inequality across households (Fernández and Rogerson, 2001; Greenwood et al., 2014, 2016; Mare, 2016; Chiappori et al., 2017; Hryshko et al., 2017; Ciscato and Weber, 2020; Calvo et al., 2024). Other papers argue against both findings (Kremer, 1997; Breen and Salazar, 2011; Breen and Andersen, 2012; Eika et al., 2019; Gihleb and Lang, 2020). We contribute to this debate by showing that *how* educational data are used to capture relevant traits for marriage market matching influences conclusions about the interplay of marital sorting and inequality.

We leverage rich administrative data from Denmark to go beyond the usual educational categories based on either levels (e.g., college) or fields of study (e.g., Social Sciences). Motivated by models of household behavior in which families value education due to its earnings potential, we develop a novel categorization that captures differences in the *labor market returns* to human capital across educational *programs* (e.g., Economics). Specifically, we group more than 1800 educational programs into four categories that exhibit similar *wage dynamics*, as summarized by the average starting wages, w_0, and average wage growth, g, of graduates. These measures map directly into the labor market payoffs of each program: w_0 captures the price of human capital, and wage growth g reflects the returns to career-shaping choices. In this sense, w_0 and g are sufficient statistics for the labor-market value of graduating from a specific educational program per unit of time supplied. We interpret differences in this value across programs as reflective of graduates' potential for labor market success and *career ambition*.

Since household resources are determined by *returns* to human capital that differ across programs, it is natural to ask whether household income inequality has been affected by changes in the composition of households based on these very returns. Using our categorization, we find that PAM increased substantially between 1980–2018 (by 20%), and changes in the overall composition of households account for 35% of the increase in income inequality over this period. In contrast, PAM by educational levels or fields exhibits no trend since the mid-1990s and the changing composition of households based on these categorizations can account only for a small fraction of inequality growth. Alternative classifications based on work hours or lifetime earnings show no trend in PAM either, which suggests that spouses increasingly sort on labor market returns per work hour rather than work schedules or lifetime income.

Methodologically, we build on the literature that emphasizes heterogeneity in labor market outcomes across education programs (Altonji et al., 2014, 2016) and exploit detailed data on labor market outcomes of graduates at the level of the educational program. Programs are defined based on ISCED codes, which identify more than 1800 unique education programs in Denmark. Examples include the vocational training of *carpenters*, professional degrees held by *nurses*, and 5-year university degrees in *law* and *business*. We define four types by grouping programs based on similarity of wage dynamics for typical graduates—average starting wages and wage growth—using k-means clustering, a well-established and popular partitioning method in machine learning and computer science (Steinley, 2006). This method has recently been introduced to economic research (Bonhomme and Manresa, 2015) and applied to categorize worker and firm types in the labor market (Bonhomme et al., 2019, 2022). To our knowledge, we are the first to apply this method to construct education-based types to study marriage market matching. Our method allows us to collapse multiple wage moments into one type and thereby simplify the analysis of assortative matching.[1]

In the first part of our analysis, we show that our method successfully clusters education programs into four clearly distinct groups based on whether starting wages and wage growth are high or low. We label our categorization *educational ambition* because we interpret the four groups as capturing differences in the potential for labor market success, which we also confirm in the data. In contrast, groups based on educational *levels* or *fields* mask significant heterogeneity in starting wages and wage growth.

In the second part of the analysis, we compare trends in assortative matching across categorizations and study how the composition of households contributes to the rise in between-household inequality. To this end, we consider the role of *trends* along three margins that influence marital sorting as reflected by *the composition of households*: the marginal distributions of education-based types by gender, the share of singles by gender and education (the *extensive margin*, i.e., who marries), and the frequency of couples by spouses' joint education types (the *intensive margin*, i.e., who marries whom).

Our first main finding is that the degree of assortative matching has increased significantly based on educational ambition, but has remained stable based on educational levels or fields. Thus, conclusions about assortative matching trends crucially depend on the categorization. To study these trends in PAM and compare them across categorizations, we follow Eika et al. (2019), Almar and Schulz (2024), and Chiappori et al. (2025). We measure the degree of

[1]Multidimensional sorting in labor and marriage markets has been explored, for example, by Lindenlaub (2017), Ciscato and Weber (2020), Low (2024), Foerster et al. (2024), and Chiappori et al. (2024).

PAM by the weighted sum of the matching frequencies of same-type couples relative to random matching (likelihood ratios).

Our second main finding is that changes in the three marriage market margins based on educational ambition contribute substantially more to the overall increase in income inequality between 1980 and 2018 in Denmark than changes in household composition based on educational level or field. Methodologically, we follow DiNardo et al. (1996) and Fortin et al. (2011) and compare observed between-household inequality measures by year to counterfactual measures that we calculate by re-weighting households such that their composition stays fixed as in 1980. Note that the degree of assortative matching is also held fixed in this counterfactual. We further assess the separate roles of trends in the marginal type distributions and marital choices to explain inequality. To this end, we follow Chiappori et al. (2020a) and combine our counterfactual re-weighting method with a structural marriage market matching model of the Separable Extreme Value (SEV) type (Choo and Siow, 2006; Chiappori et al., 2017, 2020b, 2022), which allows us to decompose changes in the composition of households into changes in the value of marriage relative to remaining single (marital surplus) and changes in the marginal type distributions. We find that the evolution of marital surplus contributes equally to the rise in inequality, regardless of how we construct types. In contrast, changes in the marginal distributions mitigate inequality through the lens of education levels or fields—but not based on educational ambition.

We complement our analysis by considering two alternative ways to measure the labor market returns of educational programs. First, we consider the similarity of graduates' typical working hours and their irregularity. Second, we group programs based on average lifetime earnings. We show that these classifications deviate substantially from our ambition baseline because they fail to capture differences in the returns to work hours and across career paths that generate similar lifetime earnings. Consequently, these classifications understate the increase in positive assortative matching relative to our benchmark.

Our findings are also robust to a variety of alternative ways of constructing ambition types. In particular, we construct gender- and cohort-specific ambition types, vary the numbers of types, and use alternative clustering variables, e.g., part-time penalties (Goldin, 2014) or manager premia. Our approach is also robust to using more aggregated units of observation at educational levels by sub-fields, which showcases the broader applicability of our method.

We contribute to the literature on the value of college degrees in the marriage market (Kirkeboen et al., 2022, 2016; Artmann et al., 2021; Nielsen and Svarer, 2009; Wiswall and Zafar, 2021; Seiver and Sullivan, 2020; Han and Qian, 2022). Unlike these papers, our measure of educational ambition considers programs from all levels of education—from compulsory schooling to graduate school—allowing us to study trends in the composition of households for the broad population. Furthermore, we build on the literature that underscores the value of (permanent) income for assortative matching (e.g., Chiappori et al., 2022) and contribute a measure that differentiates between career paths.

Moreover, we contribute to the debate on the relationship between trends in marriage market sorting and inequality by showing that the choice of how to map data on educational attainment into types affects the conclusions. All three categorizations of education-based types that we consider—ambition, levels, and fields—use information from the most advanced program that individuals graduated from. Still, conclusions about how the composition of households has changed and influenced inequality differ significantly. First, the literature that considers the level of education (Breen and Salazar, 2011; Breen and Andersen, 2012; Greenwood et al., 2014; Eika et al., 2019; Chiappori et al., 2020a) and the field of study (Seiver and Sullivan, 2020; Artmann et al., 2021; Han and Qian, 2022) yields mixed results. In contrast, our novel ambition types reveal an upward trend in positive assortative matching and a significant contribution of changing household composition to the increment in inequality. Second, we build on Burtless (1999) and Chiappori et al. (2020a) and include trends in single-headed households into our analysis of the link between family composition and income inequality. We extend their work by showing that trends in single shares by education and gender differ depending on how education-based types are defined, and this partly explains the differences in conclusions about the link between household composition and inequality across categorizations.

Finally, our insight that the categorization of types matters to capture the relationship between marriage market sorting and inequality can inform the literature on the link between assortative matching and inter-generational mobility (Bailey and Lin, 2022; Binder et al., 2022; Gayle et al., 2015). Because these studies compare groups defined by, for example, race or income, the definition of the trait on which people sort in the marriage market is potentially important for their conclusions as well.

2 Data

We use register data for the entire population of Denmark in the period 1980–2018. The data are a yearly panel and unique person identifiers allow us to combine information on individuals' education, marital status, fertility, labor market outcomes, and the identity and characteristics of their marriage or cohabiting partner (BEF, Statistics Denmark, 1980–2018).

We add information on work hours from the Danish Labor Force Survey (LFS) (LFS, Statistics Denmark, 2000–2018) for a subset of workers. We next describe the key variables we construct for our analysis and provide further details in Online Appendix A.

The sample includes all residents aged 19–60 from 1980 to 2018, with on average about 3 million individuals per year, of whom around 1.8 million are individuals in opposite-sex couples (married or cohabiting). In this sample, we measure individual education as the most advanced completed *educational program*, defined by four-digit ISCED codes (about 1,800 programs in Denmark, UDDA, Statistics Denmark (1980–2018)).[2] The most popular programs include vocational degrees such as *bank advisor*, *carpenter* or *office clerk*, bachelor's degrees like *nurse* or *pre-school teacher*, and master's degrees in *business*, *law* or *medicine*.[3]

For our main categorization, we use program graduates' *hourly wages* from the employment register (IDAN, Statistics Denmark, 1980–2018) and compute program-level wage outcomes after residualizing log wages on year dummies (with base year 2000) to remove time effects.[4] The representative LFS (2000–2018)[5] provides exact work hours and indicators for evening, weekend, and overtime work, which we use for an alternative hours-based categorization.

We analyze income inequality at the household level, considering both singles and opposite-sex couples. Our measure of household income is yearly labor income from both regular employment and self-employment according to the income register (IND, Statistics Denmark, 1980–2018). For couples, we use the sum of both spouses' income and apply the OECD equivalence scale to make one-person and two-person households comparable.

3 Ambition Types

Previous research has established that education is a valuable trait in the marriage market. It predicts both earnings potential and future time investments into career and family (Chiappori et al., 2018; Gayle and Shephard, 2019; Calvo, 2023; Calvo et al., 2024; Reynoso, 2024). In this section, we construct a wage-based categorization of educational programs that reflects heterogeneity in life-cycle returns to human capital and the prospects for labor market success across programs. Importantly, different wage dynamics across programs allow us to distinguish

[2] We exclude 2.6% of individuals with missing education information.

[3] Some programs are tied to one particular university and thus location, but most programs are spread around the country. We distinguish university degrees by institutions in an extension; see Online Appendix B.5.

[4] Hourly wages are calculated based on administrative information on labor income and hours worked in the employment register. Hours worked reflect contractual hours, i.e., part-time work is captured but not overtime.

[5] Approximately 72,000 participants are surveyed on an annual basis. The sample is weighted to ensure that it is representative of the entire population of Denmark.

the returns of different career trajectories. In turn, these returns capture the opportunity cost of time at home. In contrast, common definitions of education based on educational level or field of study mask substantial heterogeneity in wage dynamics, which we find to be crucial for understanding trends in assortative matching and inequality.

3.1 Conceptual Framework

To construct education-based types, suppose that men and women are distinguished by their education program, $i \in \mathcal{P} = \{Program_1, Program_2, ..., Program_I\}$. I is the total number of programs. Each program i is characterized by an N-dimensional vector of observable characteristics, $x_i = (x_{1i}, x_{2i}, ..., x_{Ni})$, and a dataset at the program level is defined as $x: \{x_i\}_{i \in \mathcal{P}}$. Examples of such characteristics include the length of the educational program, the field of study, the level of education, and the labor market outcomes of graduates.

For both tractability and ease of interpretation, education programs are commonly grouped into a small number of types based on their similarity in *selected* characteristics, $\tilde{x} \subset x$. Formally, let $\mathcal{T}_{\tilde{x}} : \tilde{x} \rightarrow t = \{Type_1, Type_2, ..., Type_T\}$ be a mapping that defines $T << I$ *types* by grouping the I programs based on their similarity in the sub-vector of observable characteristics $\tilde{x}$.

The literature commonly uses the mapping $\mathcal{T}_{Levels}$, which maps programs based on similarity in one characteristic, namely, their level of education (see, e.g., Fernández and Rogerson, 2001; Greenwood et al., 2014, 2016; Eika et al., 2019). One way to implement this mapping is to choose four types, $t^{Levels} = \{Primary, Secondary, Bachelor, Master\&PhD\}$. Another popular one-dimensional mapping is $\mathcal{T}_{Fields}$ (see, e.g., Seiver and Sullivan, 2020; Artmann et al., 2021; Kirkeboen et al., 2022; Han and Qian, 2022). It focuses on post-secondary education and groups programs by field of study, mapping the narrow fields of individual programs, $\tilde{x}_i = field_i$, into broader groups of fields (e.g., STEM, health, humanities, social sciences, business). This yields the mapping $t^{Fields} = \{Field_1, Field_2, ..., Field_T\}$.

3.2 Construction of Ambition Types

We take advantage of our rich data and construct the ambition types using average labor market outcomes of graduates at the program level. We use the *average starting wage*—denoted by w_0—and *average wage growth over the early career*—denoted by g.

Formally, for each of the more than 1800 programs of education i we observe $\tilde{x}_i = (w_{0,i}, g_i)$, calculated using information on all individuals who completed their education after 1980. As explained in more detail in Online Appendix A.2, we first residualize log hourly wages and then compute w_0 as the average hourly wage of program graduates during the first five years in the labor force.[6] To calculate average wage growth, g, we measure the percentage change between w_0 and w_1, where w_1 is the average hourly wage of program graduates in years 9-11 in the labor force.[7] We average across years for both w_0 and w_1 to smooth out year-to-year variation that is unrelated to worker productivity.

In our benchmark analysis, we construct four types using the mapping $\mathcal{T}(w_0, g)$. To implement the mapping, we cluster programs based on standardized starting wages and wage growth using the k-means algorithm (Steinley, 2006). This method minimizes the within-cluster variation in the two dimensions and thus produces homogeneous groups in terms of starting wages and wage growth. We denote this mapping $\mathcal{T}_{Ambition}$, which includes the following four types:

$$t^{Ambition} = \{(low\ w_0, low\ g), (high\ w_0, low\ g), (low\ w_0, high\ g), (high\ w_0, high\ g)\}.$$

Panel (a) in Figure 1 plots the mapping $\mathcal{T}_{Ambition}$. It shows how the program-specific (w_0, g) tuples map into our ambition types. The plot locates approximately 1800 programs in the space of standardized starting wages (horizontal axis) and standardized wage growth (vertical axis). We distinguish the resulting four types with different colors and markers. The mapping delivers groups that are clearly (and by construction) distinguished by whether starting wages and wage growth are low or high. Our interpretation is that graduates from high-starting-wages/high-wage-growth programs signal *career-ambition* in the marriage market by their choice of educational program. Thus, we label our categorization *educational ambition*.

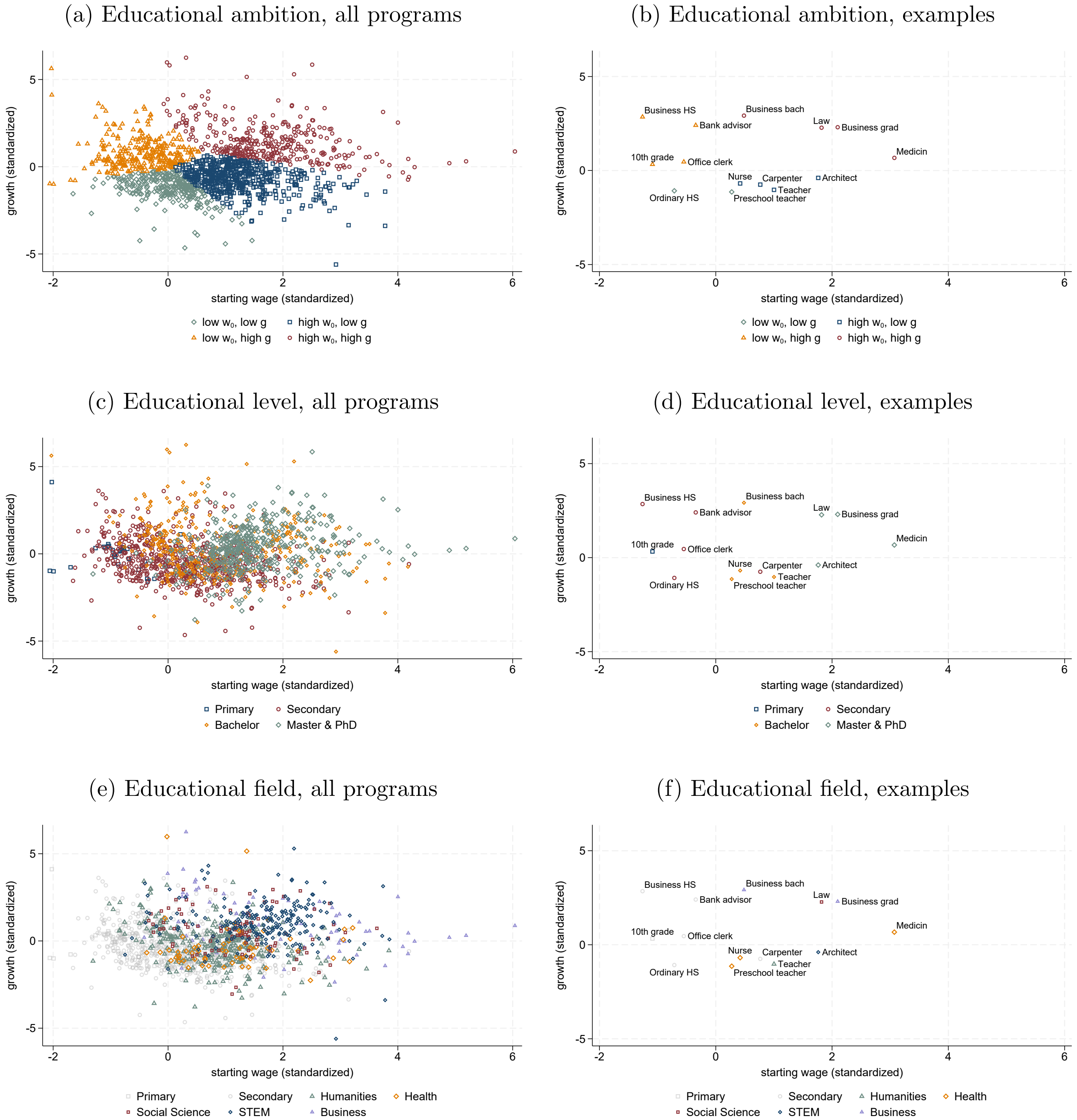
Online Appendix Table A.1 describes the four educational ambition types by population shares, gender, income, and parental wealth. Roughly 10% of the sample are in the high-starting-wages/high-wage-growth group. Men are over-represented in the categories with high starting wages, which also consist of individuals with wealthier parents.

For comparison with previous studies, we show the same plot for the mappings $\mathcal{T}_{Levels}$ and $\mathcal{T}_{Fields}$, closely following their definitions in the literature. In panels (a), (c), and (e), the position of all educational programs in the (w_0, g) is identical, but Panels (c) and (e) assign those programs to different color-marker groups depending on the level or post-secondary field of eduction, respectively. $\mathcal{T}_{Levels}$ groups programs based on educational level, i.e., Primary (compulsory schooling), Secondary (high school and vocational degrees), Bachelor (tertiary degrees of four years or less), and Master & PhD (tertiary degrees of five years or more). To

[6] 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.

[7] We focus on the first 9-11 years because wage profiles stabilize later in one's career (Bhuller et al., 2017).

Figure 1: Education-Based Types and their Starting Wages and Wage Growth



Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The horizontal axis corresponds to the standardized w_0 and the vertical to the standardized g. Points in panels (a), (c), (e) locate all educational programs with at least ten graduates in 2018—described in Section 2—along these two dimensions. Panels (b), (d), (f) show 14 large programs based on the number of graduates observed in the sample in 2018. Colors and markers uniquely assign each program to an education type, depending on the panel's definition.

construct $\mathcal{T}_{Fields}$ without losing non-tertiary programs, we keep the primary and secondary categories from $\mathcal{T}_{Levels}$ but subdivide the tertiary category based on five post-secondary fields: Humanities, Health & Welfare, Social Science, STEM, and Business.

Types constructed based on the level or field of education overlap substantially in the two wage outcomes (w_0, g), and therefore mask important heterogeneity in labor market returns. For example, in Panel (c) for level, starting wages are on average low for Primary (blue squares) and high for Master & PhD (gray diamonds), but many Secondary (red circles) and Bachelor (small orange diamonds) programs have higher starting wages than many Master & PhD programs, and wage growth within each type is widely dispersed. In Panel (e) for fields of study, graduates from STEM (blue diamonds), Business (lilac small triangles), and Social Science (red squares) programs are relatively similar in terms of average wage growth but the variation in starting wages within each group is vast.

To obtain a sense of which specific educational programs are included in the respective clusters, Panels (b), (d), and (f) locate 14 large programs in the (w_0, g) plane for the ambition, levels, and fields mappings, respectively.As an example, consider graduates from 5-year business and architecture programs, which face different labor market returns—architects exhibit lower wage growth than business graduates—and are therefore assigned different ambition types. However, they are in one group according to the level of education.

Online Appendix Table A.2 complements this example with a cross-tabulation of ambition types and levels or fields. 10% of graduates who can expect high starting wages and growth do not have a tertiary but a secondary degree. At the same time, more than 40% of individuals in the high-starting-wages/low-wage-growth group have a tertiary degree. This clearly shows that graduating from a university does not guarantee high wage growth. Moreover, Social Science, Business, and STEM fields dominate the group with high starting wages and growth. However, graduates with degrees from the Humanities or Health & Welfare are most commonly found in the groups with low wage growth and either high or low starting wages.

3.3 Alternative Measures of Human Capital

If families value education due to returns on human capital, it is natural to consider two alternative ways of capturing the human capital content of educational programs: the lifetime earnings and labor supply patterns of graduates. First, we use a one-dimensional k-means clustering and identify four groups of programs from low lifetime earnings to high lifetime earnings. Second, we use the LFS and characterize a subset of educational programs based on the fractions of graduates who work part-time or who report working irregular hours (evening, weekend, overtime). In Appendix A.4, we show that there is some overlap between these two categorizations and ambition types, but they capture returns to human capital less precisely. For example, programs whose graduates report working long and irregular hours do not necessarily come with high wage growth. Some low-wage-growth programs (e.g., teachers, architects) also fall into this category.

3.4 Education-Based Types and Career and Family Outcomes

Finally, we analyze how the different definitions of education relate to career and family outcomes. In Appendix A.5, we first construct seven proxies for career and family outcomes of graduates by educational program, including the wage penalty for part-time work, the fraction of graduates who reach a managerial position, and average accumulated wealth. We use regression analysis to show that the two building blocks of our ambition types—the wage measures w_0 and g, which capture returns to human capital in the labor market—are significantly correlated with these career and family outcomes. Importantly, most coefficients on wage moments remain significant even after controlling for education level, field of study, life-time earnings, and work hours (see Table A.3). We conclude that wage dynamics can explain long-term career and family outcomes even conditional on these widely-used human capital measures.

4 Trends in Assortative Matching

We show that the degree of assortative matching on ambition has increased over time, while assortative matching on educational levels or fields has remained constant since the mid-1990s.

Empirically, the degree of positive assortative matching (PAM) manifests itself as a positive association of spousal types in the cross-section, conditional on marriage. This association can be measured based on correlation coefficients, distance measures, or the frequency distribution of spousal types among couples. However, determining whether PAM has *changed over time* has proven elusive because the educational composition of households evolves for three reasons: (i) changes in the educational attainment of men and women (i.e., the gender-specific *marginal distributions* of education); (ii) changes in singlehood and marriage by gender and education (i.e., the extensive margin decision, *who marries*); and (iii) changes in the joint distribution of husbands' and wives' education (i.e., the intensive margin, *who marries whom*).

Indeed, in Appendix B.1, we show heterogeneous trends in these three margins for all educational categorizations. For example, we observe an increasing number of highly-ambitious individuals, particularly women, which could mechanically increase the probability that two high-type spouses meet and form a couple. Therefore, a more refined measurement of assortative matching is necessary. We employ a measure that is based both on the shares of same-type couples and the marginal type distributions conditional on marriage: the likelihood ratio (Eika et al., 2019; Chiappori et al., 2025). This measure compares the observed probability that a man of a given type is married to a woman of the same type to that probability under random matching, which is captured by the product of the type-specific shares of men and women in the married population.

Let $P^M(t_m, t_f)$ denote the fraction of married couples of type (t_m, t_f) with male type t_m and female type t_f. Let the fraction of married men of type t_m be denoted by $P^M(t_m)$ ($P^M(t_f)$ is the analogous object for married women). For each couple type (j, j') with $t_m = j$ and $t_f = j'$, the likelihood ratio is defined as follows:

$$s\left(j, j'\right) = \frac{P^M\left(t_m = j, t_f = j'\right)}{P^M\left(t_m = j\right) P^M\left(t_f = j'\right)}, \tag{1}$$

where the one-dimensional types $t \in \{1, \ldots, j, \ldots, T\}$ are the categories defined in Section 3.1: educational level, field, or ambition. The measure relates the observed frequency of a couple type (the numerator) to the expected frequency under random matching (the denominator). A likelihood ratio greater than one implies that more couples form than predicted by random matching. For same-type couples, $(j = j')$, a ratio above one indicates PAM.

We then construct aggregate measure $\mathcal{S}$ as the weighted sum across the type-specific likelihood ratios of same-type couples,

$$\mathcal{S} = s\left(1,1\right) \times \pi_1 + s\left(2,2\right) \times \pi_2 + \cdots + s\left(T,T\right) \times \pi_T \tag{2}$$

with weights $\{\pi_1, \ldots, \pi_j, \ldots, \pi_T\}$, $\sum_{j=1}^{T} \pi_j = 1$, and T is the total number of categories. Chiappori et al. (2020b) suggest to compute the weights as a convex combination[8] of the male and female married-population shares for type j:

$$\pi_j = \lambda P^M\left(t_m = j\right) + (1 - \lambda) P^M\left(t_f = j\right). \tag{3}$$

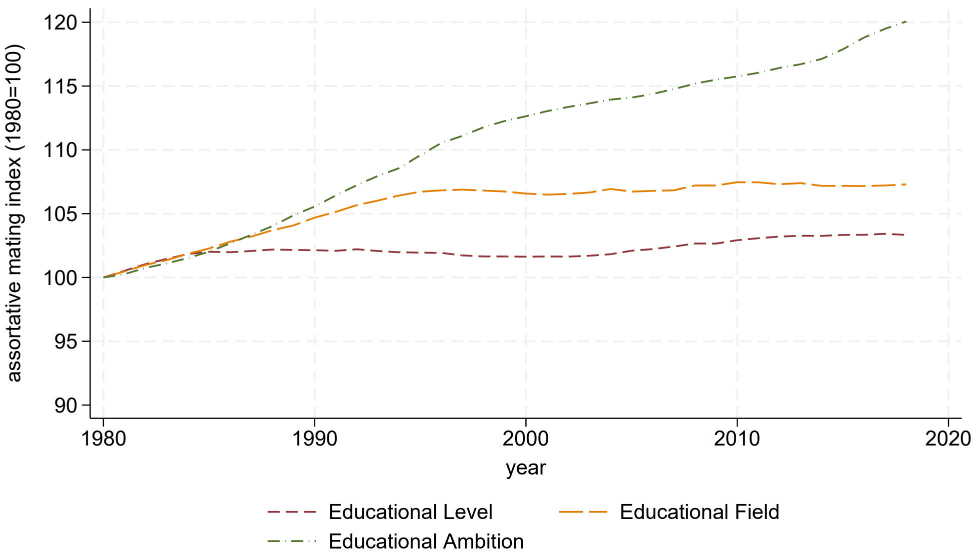
We implement the method by Almar and Schulz (2024) to compute the value of λ that minimizes mechanical distortions caused by changing type distributions, and we use the modal value for λ across years for comparability (see Appendix A.6 for details).

Figure 2 shows the aggregate trends in assortative matching for educational levels (red dashed), fields (orange long dashed), and ambition (green dash-dotted). To facilitate comparison, we index all trends such that 1980 = 100.[9]

[8] The weighted sum of likelihood ratios using this weighting scheme fulfills the formal criteria discussed in Chiappori et al. (2020b).

[9] Because marginal distributions affect $\mathcal{S}$, its levels are not comparable across markets or categorizations. For

Figure 2: Increasing Assortative Matching based on Educational Ambition



Notes: Shows the assortative matching measure $\mathcal{S}$ (see Equation (2)) for educational levels (red short-dashed line), educational field (orange long-dashed line), and educational ambition (green dash-dotted line). Normalized such that $\mathcal{S}$ in 1980 is 100. Types are constructed as explained in Sections 3.1 and 3.2.

We find PAM and a strong increase in assortative matching based on educational ambition. Relative to random matching, the likelihood of observing couples with the same ambition type has increased by approximately 20%. In contrast, based on educational levels, we find that PAM has increased by around 3% since 1980, consistent with the flat trend for the US documented by Eika et al. (2019). Based on educational-field types, we find that PAM has increased a bit more (around 7% since 1980), but the trend is flat from the mid-1990s onward.

The difference in trend based on educational levels/fields on the one hand and educational ambition on the other is explained by the differential evolution of the underlying likelihood ratios (1), plotted for all categorizations in Figure B.5 in their unweighted (Panels (a), (c), and (d)) and weighted (Panels (b), (d), and (e)) versions.[10]

For educational levels, the "secondary" category shows an unweighted likelihood ratio that is just slightly above one and flat, indicating that PAM among individuals with secondary education is neither pronounced nor increasing over time. Moreover, the weighted likelihood ratios reveal that the flat trend of the "secondary" group dominates the aggregate trend for educational levels. The tendency to sort decreases in the growing tertiary categories and increases in the shrinking primary education category, but these trends cancel each other out, so there

example, two markets with different education shares but only same-education couples have the same degree of PAM but different $\mathcal{S}$. Yet, our weighting strategy makes the trend within categorization interpretable. Appendix Figure B.4 shows non-indexed trends in $\mathcal{S}$, indicating PAM for all three categorizations ($\mathcal{S} > 1$).

[10]Note that the weighted trends add up to the aggregate trends in levels displayed in Figure B.4.

is almost no change in $\mathcal{S}$ for levels.

Any difference between trends for levels and fields in Figure 2 comes from tertiary fields because the primary and secondary categories overlap with the levels categorization. The type-specific likelihood ratios are positive and decreasing in all tertiary fields, similar to the trends for "Master & PhD" (educational levels). For men, the composition of graduates across fields is relatively stable (Figure B.1, Panel (e)). For women, "Business", "STEM", and "Social Sciences" expand (Figure B.1, Panel (f)), and their weighted likelihood ratios reveal that they contribute to increasing PAM. However, "Health" and "Humanities" dominate in size, and the weighted measures for these fields decrease after 2000, flattening the aggregate trend.

For educational ambition, the unweighted likelihood measures suggest that PAM is pronounced in the category with high starting wages and high wage growth. Although the unweighted likelihood ratio is decreasing over time, the increasing size of this group, especially for women (Figure B.1, Panels (c) and (d)), means that the likelihood of a match among highly ambitious individuals becomes more and more important for the aggregate trend, as revealed by the weighted ratios. We find a stable second-highest likelihood of a match in the category with low starting wages and low wage growth. This group also increases in size and, therefore, contributes substantially to the positive aggregate trend. This is in stark contrast to the shrinking group of individuals with lowest educational level (compulsory schooling). The low-low ambition types include occupations like preschool teachers and physical therapists with secondary or tertiary levels of education, which are growing due to increasing labor demand from the public sector. The other two educational ambition categories exhibit unweighted likelihood ratios close to one. The category with low starting wages but high wage growth shrinks over time, curtailing its influence on the aggregate measure. The category with high starting wages and low wage growth plays the smallest role for the aggregate trend. Taken together, these developments explain the 20% increase in PAM based on educational ambition.[11]

[11] As a robustness check, we also consider (log) odds ratios. The odds ratio has some desirable properties (Chiappori et al., 2025) but is local in nature, so interpretation is more involved relative to the aggregate measure $\mathcal{S}$. We calculate it for all the (2×2) submatrices with same-type couples on the diagonal, following Table 6 of Chiappori et al. (2020a). For education levels, all odds ratios decreased between 1980 and 2018. For ambition, we see an even split of increasing and decreasing odds ratios. Consistent with the documented increase in the weighted sum of likelihood ratios, we find that the submatrices with increasing (decreasing) odds ratios cover a larger (smaller) share of the 2018 marriage market.

5 The Marriage Market and Inequality

In this section, we show that the evolution of the composition of households by education affects inequality, but conclusions about the magnitude of this effect depend greatly on the categorization (levels, fields, or ambition). To study the link between the evolution of the composition of households and income inequality for different categorizations, we first use the semi-parametric decomposition technique of DiNardo et al. (1996) (DFL) to quantify how the composition affects inequality along all margins. Second, we combine DFL with the marriage market matching model of Choo and Siow (2006). This allows us to assess the contribution of different margins of marriage market matching (marginal distributions and marital surplus) to raising income inequality between households.[12] Our decomposition builds on Chiappori et al. (2020a), who use a structural model to link marital sorting and inequality. This approach allows us to incorporate both married couples and singles into the analysis.

In Subsection 5.1, we apply the DFL approach to quantify the importance of the changing composition of households. In a nutshell, scenario (i) computes counterfactual income inequality at any year τ by keeping fixed at a baseline year the composition of households along all margins (marginals, who marries, and who marries whom). This approach guarantees that at any year τ the degree of assortative matching $\mathcal{S}$ is as in the base year, which helps us to link trends in assortative matching to trends in inequality.

In Subsection 5.2, we use a structural marriage market matching model of the Separable Extreme Value (SEV) type (Choo and Siow, 2006) to differentiate between (ii) changing gains from marriage (marital surplus), which affect both the intensive and extensive margin, and (iii) changing marginal type distributions.[13]

5.1 Fixed Household Composition

Let $\mu_{\tilde{x}}$ represent the marital frequency matrix of all types of households—married and single—according to the education categorization resulting from mapping $\mathcal{T}_{\tilde{x}}$, based on characteristics $\tilde{x}$. Note that $\mu_{\tilde{x}}$ is determined by the marginal distributions of types, who marries (the exten-

[12] An alternative way to generate counterfactual household compositions is an algorithmic approach as suggested by Mosteller (1968), and, more recently, Greenwood et al. (2014) and Eika et al. (2019). Our qualitative results are robust to using the algorithmic approach, see an earlier version of this paper (Almar et al., 2023).

[13] Note that we require additional structure on how individuals choose partners because we cannot fix one margin and determine the other two. This is due to feasibility conditions in the marriage market, which only restrict the allocations to be such that the total mass of individuals of any education type equals the sum of married and single individuals of that type. For example, if we fix the marginal distributions of education at the 1980 level, a decision model is needed to assign individuals into counterfactual fractions of couples and singles by educational type.

sive margin), and who marries whom conditional on marriage (the intensive margin). To reduce notation, in what follows we omit the subscript $\tilde{x}$ when clear from context. Let $\tau \in [1980, 2018]$ denote year, and τ_y and τ_μ denote the year in which household income y and the marital frequency table μ are measured, respectively. Let the distribution of household income conditional on household education types in year τ_y be denoted by $F_{Y|\mu}(y|(t_m, t_f), \tau_y)$.

To analyze how income inequality would have developed had the composition of households remained unchanged, we keep μ fixed at base year τ_μ, while letting the household income distribution F_Y change to some year τ_y. The counterfactual income distribution when income is measured in year τ_y and the household composition is fixed at year τ_μ is:

$$\widehat{F_Y}(y|\tau_y, \tau_\mu) = \int F_{Y|\mu}(y|(t_m, t_f), \tau_y)\psi_{\tau_y,\tau_\mu} d\mu((t_m, t_f)|\tau_y). \tag{4}$$

Importantly, the factor ψ_{τ_y,τ_μ} allows us to re-weight households in the τ_y data to reflect their frequency had the marriage market stayed at its τ_μ composition. Specifically,

$$\psi_{\tau_y,\tau_\mu} = \frac{d\tilde{\mu}((t_m, t_f)|\tau_\mu)}{d\mu((t_m, t_f)|\tau_y)}.$$

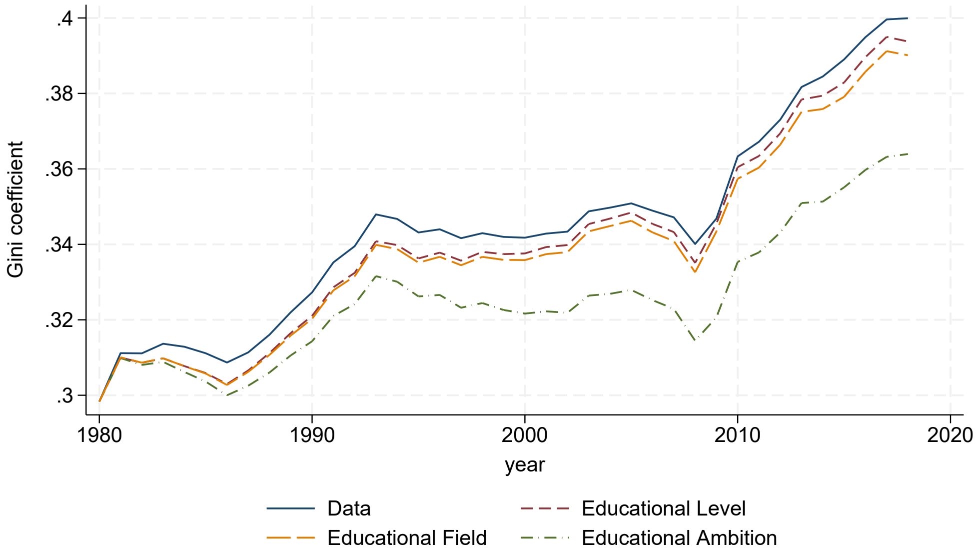
The denominator of the re-weighting factor reflects the composition of households in the observed year τ_y. In practice, we estimate this denominator as the probability of observing household type (t_m, t_f) in year τ_y, which we denote by $P_\mu((t_m, t_f)|\tau_y)$. The numerator, in turn, reflects the *counterfactual* composition of households had the marriage market stayed at its τ_μ composition. We follow DiNardo et al. (1996) and Fortin et al. (2011) and estimate the numerator using the probability of observing household type (t_m, t_f) in year τ_μ, which we denote by $P_\mu((t_m, t_f)|\tau_\mu)$. Hence, in equation (4) we substitute the estimated re-weighting factor

$$\widehat{\psi}_{\tau_y,\tau_\mu} = \frac{P_\mu((t_m, t_f)|\tau_\mu)}{P_\mu((t_m, t_f)|\tau_y)}. \tag{5}$$

for ψ_{τ_y,τ_μ}. Intuitively, household types that are more (less) common in τ_y than in τ_μ get a weight lower (greater) than one in the counterfactual income distribution. We compute the counterfactual income expression (4) and re-weighting factor (5) when $\tau_y = \tau \in [1980, 2018]$ and $\tau_\mu = 1980$: $\widehat{F_Y}(y|\tau_y = \tau, \tau_\mu = 1980)$ and $\widehat{\psi}_{\tau_y=\tau,\tau_\mu=1980}$. In this counterfactual scenario, the configuration of households stays at its 1980 level for any year τ in which we measure income. Importantly, our choice of weights guarantees that those who are married in year τ exhibit the degree of assortative matching $\mathcal{S}$ of the 1980 households.[14]

[14]In Appendix A.7, we show this result formally. Additionally, our choice of weights implies that the log odds

Figure 3: Changes in Household Composition and Inequality



Notes: Shows the development of the Gini coefficient of between-household income between 1980–2018 in the data (blue solid line), and in the counterfactual scenario (i) (fixed household composition, explained in Section 5.1) for educational level (red short-dashed line), educational field (orange long-dashed line), and educational ambition (green dash-dotted line) types.

Using counterfactual household income for all education-based categorizations of types, we compute counterfactual moments of income inequality. In Figure 3, we show that if the household composition had stayed fixed as in $\tau_\mu = 1980$, household income inequality at any year $\tau > 1980$ would have been mitigated relative to the trend in the data. We plot, for all years $\tau_y = \tau \in [1980, 2018]$, the observed Gini (blue solid line) and the counterfactual Gini coefficients from scenario (i), holding household composition fixed by educational level (red short-dashed line), educational field (yellow long-dashed), or educational ambition (green dot-dashed). All counterfactual trends lie below the data, indicating that inequality would have increased less. Crucially, however, the counterfactual trend for educational ambition diverges most from the actual trend. Thus, changes in the composition of households based on educational ambition account for a larger share of increasing between-household inequality than the composition of households based on educational level or field. One reason is that highly ambitious women have increasingly entered marriage (the extensive margin), see Figure B.3. Another reason is that positive assortative matching based on educational ambition (the intensive margin) has become more pronounced, while it has barely increased based on levels and fields, recall Figure 2.

In Table 1, we decompose the total change in between-household income inequality between 1980 and 2018. Column (a) shows the results for the Gini coefficient, which summarizes in-

ratios are also held fixed at their 1980 values.

equality in the entire distribution; in columns (b) and (c) we extend our analysis and show the 90/50 and 50/10 percentile ratios, respectively. For each inequality measure, the first row contains the inequality changes in the data (Δ_{Data}). Between-household income inequality has increased according to all three measures. The Gini coefficient has increased by 0.102 (from 0.298 to 0.400), the 90/50 percentile ratio has increased by 0.322 (from 1.643 to 1.957), and the 50/10 percentile ratio has even increased by 3.626 (from 3.170 to 6.796). These changes correspond to 100%.

Panel (i) of Table 1 shows our main result: with a fixed household composition in terms of educational ambition types, the counterfactual 2018 Gini coefficient amounts to 65% of the true value. That is, 35% of the increase in the Gini since 1980 can be explained by changing household composition based on educational ambition. Using the common education-based categorizations, we do not arrive at the same conclusion. With 94% for levels and 90% for fields, the household composition matters much less for the observed inequality increment according to these categorizations.

The composition of the households based on educational ambition also stands out by explaining a greater share of increasing inequality for percentile-based measures. The increase in the 90/50 ratio is close to the factual increase based on fields and levels, but based on educational ambition it would only have increased by 50%. For the 50/10 ratio, the increase is even mitigated by the changing composition of households through the lens of levels and fields, while the compositional changes in terms of ambition amplified household income inequality in the lower half of the income distribution.

Overall, these differences highlight our main contribution: how we define education-based types matters for conclusions on how the marriage market affects inequality between households.

5.2 Fixed Marital Surplus vs. Fixed Marginal Distributions

We investigate what particular aspect of the marriage market contributed to amplifying the increase in household income inequality. Because the supply of education-based types, the decision to marry, and the decision of whom to marry are endogenously related, disentangling their contribution requires additional structure. We follow the literature (Choo and Siow, 2006; Dupuy and Weber, 2022; Chiappori et al., 2020a,b, 2025) and use the Separable Extreme Value (SEV) model.

Specifically, we decompose the role of trends in household composition to explain changes in inequality into the contributions of changing marginal distributions of education and the

Table 1: Decomposing Changes in Income Inequality

	(a) Gini		(b) $P90/P50$		(c) $P50/P10$	
Factual change (Δ_{Data})	0.102	100%	0.322	100%	3.626	100%
	Δ_{Gini}	$\frac{\Delta_{Gini}}{\Delta_{Data}}$	$\Delta_{P90/P50}$	$\frac{\Delta_{P90/P50}}{\Delta_{Data}}$	$\Delta_{P50/P10}$	$\frac{\Delta_{P50/P10}}{\Delta_{Data}}$
(i) Fixed household composition						
Educational Level	0.095	94%	0.318	99%	4.091	113%
Educational Field	0.092	90%	0.301	93%	4.063	112%
Educational Ambition	0.066	65%	0.161	50%	2.531	70%
(ii) Fixed marital surplus						
Educational Level	0.078	76%	0.225	70%	2.417	67%
Educational Field	0.078	77%	0.221	69%	2.538	70%
Educational Ambition	0.076	75%	0.206	64%	2.547	70%
(iii) Fixed marginals						
Educational Level	0.134	132%	0.485	150%	6.953	192%
Educational Field	0.132	130%	0.471	146%	6.965	192%
Educational Ambition	0.105	104%	0.319	99%	4.808	133%
(iii.a) Fixed marginals (male)						
Educational Level	0.103	102%	0.313	97%	4.401	121%
Educational Field	0.102	100%	0.309	96%	4.419	122%
Educational Ambition	0.099	97%	0.301	93%	3.889	107%
(iii.b) Fixed marginals (female)						
Educational Level	0.129	127%	0.426	132%	5.873	162%
Educational Field	0.129	127%	0.426	132%	5.898	163%
Educational Ambition	0.108	107%	0.335	104%	4.457	123%

Notes: Panels show the counterfactual scenarios constructed as explained in Section 5.1 (panel (i)) and in Section 5.2 (panels (ii) to (iii.b)). $P90/P50$ ($P50/P10$) is the ratio of the 90th and 50th (10th) percentile in the income distribution. Δ_{Data} shows the observed inequality changes. $\Delta_{Gini}/\Delta_{Data}$ is the counterfactual change relative to the observed change. Each row within each scenario shows the columns' statistic for one of the three definitions of types (as explained in Section 3): educational level, educational field, and educational ambition types.

evolving value of marriage relative to singlehood (marital surplus). To do so, we combine the DFL approach—which we use to construct the re-weighting factors—with the SEV structure—which allows us to isolate the role of changing marginal distributions from that of changes in the value of marriage. The framework introduced by Choo and Siow (2006) models individuals' decision of whom to marry or whether to remain single based on the value of their potential matches relative to the value of remaining single: the marital surplus. A distinctive feature is that the marital surplus is the sum of two components: a *systematic* component that only depends on the type composition of the potential couple, and a random idiosyncratic taste shock that depends only on the type of the potential partner.[15] Importantly, Choo and Siow (2006)

[15] While the advantage of Choo and Siow (2006) is its simplicity, a number of papers criticize the underlying—admittedly strong—assumptions (see, e.g., Gualdani and Sinha, 2023). One such assumption is independence-of-irrelevant-alternatives (IIA). Gutierrez (2020) relaxes IIA by modifying the Choo and Siow (2006) model and considering match-specific rather than type-specific taste shocks. We have implemented this modification and

derive a closed form relationship between the systematic component of the marital surplus of couple type (j,j')—which we denote by $\Pi_{jj'}$—and the ratio of the observed share of couples type (j,j') and the geometric average of the single shares of type j and j':

$$\Pi_{jj'} = \frac{P_\mu\left(t_m = j, t_f = j'\right)}{\sqrt{P_\mu\left(t_m = j, t_f = \emptyset\right) P_\mu\left(t_m = \emptyset, t_f = j'\right)}}, \tag{6}$$

where $P_\mu(t_m = j, t_f = \emptyset)$ ($P_\mu\left(t_m = \emptyset, t_f = j'\right)$) is the probability of observing a man of type j (women of type j') without a partner.

We combine the marital surplus (6) with the feasibility conditions in the marriage market whereby the mass of individuals of type t equals the sum of the mass of individuals of that type who marry and remain single. We denote the mass of single women type t_f and of single men type t_m by $P_\mu(\emptyset, t_f)$ and $P_\mu(t_m, \emptyset)$, respectively. For a particular categorization based on $\tilde{x}$, we denote the mass of women type t_f and the mass of men type t_m, respectively, by

$$\begin{aligned} P_{\tilde{x}}(t_f) &= \sum_{t_m} P_\mu(t_m, t_f) + P_\mu(\emptyset, t_f) \\ P_{\tilde{x}}(t_m) &= \sum_{t_f} P_\mu(t_m, t_f) + P_\mu(t_m, \emptyset). \end{aligned} \tag{7}$$

Formally, let $\tau_{\tilde{x}}$ be the year in which the marginal distribution of types based on definition $\tilde{x}$ is measured, and let τ_Π be the year in which the marital surplus is measured. We define the income distribution when household income is measured in year τ_y, the marginal distributions of $\tilde{x}$ in $\tau_{\tilde{x}}$, and the marital surplus Π in τ_Π as

$$\widehat{F_Y}(y|\tau_y, \tau_{\tilde{x}}, \tau_\Pi) = \int F_{Y|\mu}(y|(t_m, t_f), \tau_y)\psi_{\tau_y,\tau_{\tilde{x}},\tau_\Pi} d\mu((t_m, t_f)|\tau_y). \tag{8}$$

As in counterfactual (i) the factor $\psi_{\tau_y,\tau_{\tilde{x}},\tau_\Pi}$ allows us to re-weight households in the τ_y data to reflect their frequency had the education marginals and marital surplus stayed at their $\tau_{\tilde{x}}$ and τ_Π compositions, respectively. In this case, in which we distinguish between marginals and surplus, we have

$$\psi_{\tau_y,\tau_{\tilde{x}},\tau_\Pi} = \frac{d\widehat{\mu}((t_m, t_f)|\tau_{\tilde{x}}, \tau_\Pi)}{d\mu((t_m, t_f)|\tau_y)}.$$

Again, the numerator of the re-weighting factor is not observed, so it has to be estimated. An additional complication is that when $\tau_{\tilde{x}} \neq \tau_\Pi$, we do not have a frequency table $P_\mu((t_m, t_f)|\tau_{\tilde{x}}, \tau_\Pi, \tau_{\tilde{x}} \neq \tau_\Pi)$ as a data counterpart, because only marriage markets in which the marginal type distri-

present results for the model-based counterfactuals in Appendix Table B.2. All our conclusions are unaffected but quantitatively the role of the marriage market is slightly reduced in all scenarios.

bution and the marital surplus are measured in the same year ($\tau_{\tilde{x}} = \tau_{\Pi}$) realize. We retrieve these counterfactual frequency tables, $\widehat{\mu}$, using the model. For example, when we fix marginals (7) at time $\tau_{\tilde{x}}$ and let the marital surplus be as observed in year $\tau > \tau_{\tilde{x}}$, we use the system of equations (6) and (7) in two steps: first, we compute the *counterfactual* fractions of singles that would close the marriage market in τ when the marginal distributions are as in $\tau_{\tilde{x}}$; second, we compute the implied *counterfactual* fractions of couples. We end up with a counterfactual matching matrix, $\widehat{\mu}$, specifying the frequency of each type of household—including the singles—with elements denoted by $P^{SEV}_{\widehat{\mu}}((t_m, t_f)|\tau_{\tilde{x}}, \tau_{\Pi})$. Once we have calculated the counterfactual household compositions, $\widehat{\mu}$, in which the marginals are measured in year $\tau_{\tilde{x}}$ and the surplus in year τ_{Π}, we can estimate the re-weighting factor by

$$\widehat{\psi}^{SEV}_{\tau_y,\tau_{\tilde{x}},\tau_{\Pi}} = \frac{P^{SEV}_{\widehat{\mu}}((t_m, t_f)|\tau_{\tilde{x}}, \tau_{\Pi})}{P_{\mu}((t_m, t_f)|\tau_y)}. \tag{9}$$

and use it to compute the different counterfactual income distributions in (8).

In the fixed marital surplus counterfactual (ii), we fix marital surplus at $\tau_{\Pi} = 1980$, while we measure income and education marginals in any year $\tau > 1980$. Specifically, we use counterfactual re-weighting factor $\widehat{\psi}^{SEV}_{\tau_y=\tau,\tau_{\tilde{x}}=\tau,\tau_{\Pi}=1980}$ to obtain the counterfactual income distribution $\widehat{F_Y}(y|\tau_y = \tau, \tau_{\tilde{x}} = \tau, \tau_{\Pi} = 1980)$. Intuitively, every year $\tau > 1980$ each household—coupled or single-headed—is reweighted so that the relative frequencies of couples to singles by type and gender give rise to the gains of marriage relative to singlehood revealed in the year 1980.

In the fixed-marginals counterfactual (iii), we fix the marginal distributions of education at $\tau_{\tilde{x}} = 1980$, while we measure income and marital surplus at any year $\tau > 1980$. Specifically, we use counterfactual re-weighting factor $\widehat{\psi}^{SEV}_{\tau_y=\tau,\tau_{\tilde{x}}=1980,\tau_{\Pi}=\tau}$ and counterfactual income distribution $\widehat{F_Y}(y|\tau_y = \tau, \tau_{\tilde{x}} = 1980, \tau_{\Pi} = \tau)$. We also keep either the male (case iii.a) or the female (case iii.b) marginal type distributions fixed. In those cases, we further distinguish between marginals by gender in expressions (8) and (9).

Panel (ii) of Table 1 shows the results for the fixed-surplus scenario. When we generate households in 2018 based on the 1980 gains from marriage and the 2018 marginal distributions, we find that inequality would have increased about a quarter less than in the data. Interestingly, this result is quantitatively similar across categorizations, so differences in their evolution of marital surplus are not driving the result in scenario (i). We reach similar conclusions when we measure income inequality based on percentile ratios.

In Panel (iii) of Table 1, we first keep the marginal type distributions for both genders fixed at the 1980 level. We then repeat the exercise keeping either the male or the female marginal type distribution fixed, see Panels (iii.a) and (iii.b). The marginal distributions shifted such that the numbers of individuals in the top categories increased, and this change is more pronounced for women.[16] That is, there are more men and women who graduate with tertiary degrees and/or from ambitious educational programs in 2018 compared to 1980.

Based on the Gini coefficient in column (a) and educational levels (or fields), we find that these trends in educational attainment had a mitigating effect on inequality. Without the shift, inequality would have increased to 132% (130%) of the actual 2018 value. The mitigating effect manifests itself mainly in the lower half of the income distribution. The 50/10 percentile ratio in column (c) would have been almost twice as high. For the 90/50 ratio in column (b), we see slightly more modest mitigating effects for educational level and field types (150% and 146%). Based on educational ambition types, we do not find significant mitigation (or amplification) for the Gini or the 90-50 ratio with fixed marginals (104% and 99%), but there is a mitigation effect in the lower half of the distribution (133%).

Fixing only women's marginals at 1980 in scenario (iii.b) essentially reproduces scenario (iii) with both marginal distributions fixed across categorizations. The mitigating effects remain but become slightly weaker for level and field. By contrast, fixing only male marginals (iii.a) implies little mitigation: the counterfactual distributions nearly match the data, aside from a modest reduction in the 50/10 ratio for level and field. Thus, the mitigation is driven primarily by changes in female marginals.

The counterfactuals with fixed marginals for women highlight again the importance of distinguishing between the three categorizations: For example, while women's move into tertiary education had a considerable mitigating effect, their entry into (ambitious) high-wage/high-growth programs did not mitigate the rise in inequality. This, in turn, contributes to a larger overall role of the marriage market for inequality trends based on ambition types.

6 Alternative Categorizations and Robustness

We explore the meaning of our results further in several ways. First, we replicate our main analysis using two alternative categorizations based on lifetime earnings and labor supply moments in Appendix B.3. Trends in assortative matching on hours moments and lifetime earnings are flatter than on ambition. This suggests that the increasing spousal similarity in ambition is due to sorting on career trajectories that lifetime-income and hours-based classifications are unable

[16] The share of men (women) with long-cycle tertiary education increased by a factor of 3 (11) between 1980 and 2018. For educational ambition types, the share of men (women) in the top category doubled (increased five-fold), as shown in Figure B.1 in the Online Appendix.

to distinguish. However, changes in the composition of households based on these alternative categorizations have affected inequality more than what educational levels or fields suggest. Consistent with the results for ambition, we find that inequality growth would have been mitigated had the composition of households in terms of work hours or lifetime earnings remained unchanged. However, for these categorizations, changes in the composition of *different-type* couples have had the greatest influence on inequality.

Second, in Appendix B.5 we investigate whether our main results are robust to constructing ambition types in alternative ways. We construct ambition types by gender and by cohort, consider different numbers of clusters, use part-time penalties (Goldin, 2014) and manager premia as alternative clustering variables, and apply our approach to more aggregated data by level-and-subfield. Our conclusions do not change as long as the variables used to group units capture returns to human capital.

Third, our results remain when we exclude individuals with coarser 3-digit educational codes—commonly found for immigrants who completed studies abroad—and when we restrict the sample to individuals aged 40 to 49—who have most stable family and career circumstances.

Finally, we find a similarly important role of the marriage market for inequality based on ambition types when measuring inequality trends based on disposable income. This indicates that the main results are not substantially mitigated by taxation and transfers.

7 Conclusion

We provide new insights into the relationship between education-based marital sorting and between-household inequality. Our main finding is that conclusions about the link between household composition and inequality greatly depend on how education-based types are constructed.

We build a novel categorization of education by clustering education programs based on the wage dynamics (starting wages, early-career growth) of graduates and label the resulting categorization *educational ambition*. Going beyond alternative classifications based on educational level, field of study, labor supply patterns, or lifetime income, these ambition types are constructed to reflect differences in the labor market returns to human capital across educational programs, and they are strong predictors of family and career outcomes.

Positive assortative matching on educational ambition increased by about 20% between 1980 and 2018, while PAM on the alternative classifications remained relatively flat.

Overall, changes in the composition of households by educational ambition explain approximately 35% of the increase in between-household inequality over the same period.

Taken together, our analysis suggests that considering richer classifications than the level or field of education is a promising direction for future research on the relationship between marriage and labor markets. Various administrative data sources across countries provide long panel data with program-level information that allows researchers to implement our approach to define marital types. Furthermore, we find similar results when defining educational ambition based on more aggregate units of educational levels by subfield. This suggests that coarser data can also be used to construct ambition types, as long as those data include some information about labor market returns to human capital in the form of wage dynamics or other measures of career trajectories of graduates.

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Online Appendix

Educational Ambition, Marital Sorting, and Inequality

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A Additional Details on Data and Measurement

A.1 Data sources

All registers used are yearly population-wide data sets. We use all the persons living in Denmark at the end of a year from 1980-2018, whom are observed in the data sets PERSONER and BEF. These data sets contain yearly information on age, partner ID, municipality, gender, civil status, and number of children. We merge these data sets with additional information as follows. We measure the highest achieved education from the education register (UDDA). From the income register (IND), we measure income and wealth information, and the hourly wage earned in the primary job held in the last week of November each year (from IDAN).[17] The datasets EXPYEAR and IDAP provide information on real labor market experience. Finally, we use information from the registers RAS and AKM in order to get occupational information and a part-time/full-time indicator. When available we also merge information from the Labor Force Survey in order to get more details on flexibility and hours worked than what is available from the registers. The Labor Force Survey covers the years 2000 to 2018. We keep information on individuals aged 19 to 60.

A.2 Definition of key variables

Main Income measure Our main income variable, ERHVERVSINDK_13, measures all earned income during a year, where earned income is defined as income from employment and self-employment.

In an extension, we consider annual disposable income, which is defined as the sum of total labor income (the income variable in the main analysis), total capital income, government transfers, and the predicted rental value of self-owned housing (had it been on the rental market) minus taxes, expenditures on interest rates, and alimony for children or spouses.

[17] We rank job types and keep the highest rank available in JOB_TYPE: H, 3, A, S, M. The variable for the hourly wage is TIMELON prior to 2008 and SMAL_TIMELOEN in 2008 and after.

Hourly wage Hourly wages are imputed from administrative information on labor income and hours worked in the employment register. Hours worked reflect contractual hours, i.e., part-time work is captured but not overtime. Before 2008, the hours are reported in four discrete bins. For further details, see Lund and Vejlin (2016). After 2008 we have the exact number of contractual hours.

We run a regression of log hourly wages on year dummies and educational specific experience profiles in order to take into account an aging population and differences in educations over time. We then subtract the coefficients on the year dummies (2000 base) from the log hourly wages. This gives us our residualized log hourly wages, which is what we use for the analysis.

Education We find the highest completed education of the individuals when they are the oldest (if not reaching 35 in the data) or when they are age 35. This is the program and year of graduation we use as their (final) educational program.[18] We do not consider programs that an individual did not complete. For example, the most advanced program of high school dropouts is "Primary Education."

Educational programs As a point of departure each educational program is an ISCED code. However, in a few places we change the definition slightly. In the start of the sample we have a group of individuals who have only 7th or 8th grade, because compulsory schooling ended in 7th grade until around 1960. We pool 7th-9th grade into one group called 9th grade. We split up both 9th grade (1109) and 10th grade (1110) up into 5 sub programs each based on region of graduation.[19] Finally, some individuals have an older code for high school than those graduating in 1980 and later. We assume that the high school education did not change much and we use starting wages and wage growth for the new high school education for those who graduated with the old code prior to 1980.

Starting wages and growth Starting wages are the average of the log hourly residualized wages in years 1-5 after graduation. The growth is calculated based on the difference between the average in years 9-11 and the starting wages. This is done for each individual in the sample (both singles and couples). In order to get information on the program level we average across

[18]Note that ambition types are assigned based on the *final* program, e.g., time-invariant, whereas educational level and field types are assigned based on the highest degree achieved by a given age. This is to be consistent with the previous literature on education-based marriage market types. In practice, this distinction has a neglectable impact because most individuals finish their studies in their 20s.

[19]In particular we do the following. Use 9th grade (1109)(split by region) starting wages and growth for the following codes (all also split by region depending on where the individual lives in the first year we see them in the data, e.g., 1980): 1007,1008,1023,1123,1009,1022. Use 10th grade (1110) (split by region) for: 1010.

individuals, but condition on individuals who graduated in 1980 or later, for whom we observe both for starting wages and having wages in some of the years 9-11 after graduation. We also only use information from individuals, whose wage growth is below the 99th percentile (extreme values are likely due to measurement error).

With this in place, we can standardize starting wage and growth. All individuals in the data have been assigned the average values from their final program. We generate the standardized variables by subtracting the mean and dividing by the standard deviation.

Next, we construct our four ambition types by using k-means clustering on the standardized starting wages and growth. All individuals are still in the data set, but because everybody from the same program has the same value, we are grouping at the program level.

Work hours and flexibility We use survey responses about usual working hours from the Labor Force Survey (LFS) to construct measures of typical work schedules by program. The LFS starts in 2000 and we observe at least 50 survey responses of prime-age workers (aged 25-54) for 724 unique educational program identifiers.

Using these data, we first measure the share of graduates working *short hours*, defined as the fraction of prime-age graduates by program who work part-time. Second, we construct the share working *irregular hours*, defined as the fraction of prime-age graduates by program who report evening, weekend, or overtime work.

We then merge these program-specific measures of work schedules and hours flexibility onto the population register 2000-2018, capturing about 95% of the baseline population sample. We standardize the shares of short and irregular hours and then use our k-means clustering methodology to group the 724 programs based on their similarity in these two hours-based dimensions. Assuming stable program characteristics on work schedules over time, we assign the resulting type classification by program to individuals over the earlier part of the sample, 1980–1999 as well.

Lifetime earnings We construct average lifetime earnings based on program graduates who are observed in the labor market for at least 30 years from the time of graduation. To compute lifetime earnings, we deflate earnings by running a regression of log annual earnings, for each program separately, on year dummies (base year 2000) and dummies for years since graduation to account for compositional differences by programs in the share of graduates at different life-cycle stages.

We can measure average lifetime earnings for 502 programs that have at least 30 workers observed in the register data over 30 years since graduation. We standardize the average lifetime earnings measure and then use our k-means clustering methodology for this single dimension to group programs by their similarity in average lifetime earnings.

A.3 Descriptive statistics

Table A.1: Basic Descriptive Statistics for Educational Ambition Types

Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Population share	20.2%	22.7%	47.5%	9.7%	100.0%
Female share	64.8%	31.0%	56.0%	33.4%	50.0%
Starting wage	4.841	5.015	4.728	5.181	4.860
	(0.0613)	(0.0775)	(0.0488)	(0.134)	(0.170)
Wage growth	0.0807	0.118	0.211	0.301	0.172
	(0.0339)	(0.0436)	(0.0574)	(0.0756)	(0.0862)
Parental wealth at graduation	401347.0	664844.4	269760.8	1189937.8	474762.7
	(259668.7)	(1609532.9)	(307755.7)	(353775.9)	(858804.7)
Wage growth SD	0.323	0.298	0.430	0.365	0.359
	(0.0682)	(0.0536)	(0.0946)	(0.0731)	(0.0945)

Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The four first columns report averages of individual-level descriptive statistics for each of the four educational ambition types identified in Section 3. The final column reports the same statistics for the entire population of couples as defined in Section 2. Starting wages are measured in logs and wage growth are growth rates in hourly wages in the first ten years after graduation. Parental wealth at graduation is computed as the sum of both parents' net wealth in the year in which the individual graduates from the most advanced educational program. Deflated with base year 2000. Standard deviations in parentheses.

Table A.2: Educational Levels, Fields, and Ambition Types

Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Educational Level					
Primary	8.3%	0.5%	56.2%	0.2%	28.5%
Secondary	66.2%	57.3%	40.1%	10.3%	46.4%
Tertiary	24.9%	42.1%	8.2%	89.3%	24.9%
Educational Level within Tertiary					
Bachelor	24.1%	29.4%	3.1%	30.3%	15.9%
Master & PhD	0.8%	12.7%	0.5%	59.0%	9.0%
Educational Field within Tertiary					
Humanities	2.2%	18.0%	1.2%	2.7%	5.4%
Social Science	0.1%	3.0%	0.5%	16.4%	2.5%
Business	0.3%	0.5%	0.3%	21.4%	2.4%
STEM	0.2%	3.9%	0.2%	34.3%	4.4%
Health & Welfare	18.5%	12.3%	1.1%	11.6%	8.2%
Other	3.7%	4.4%	0.3%	3.0%	2.2%

Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The four first columns and the first panel report population shares for each of the four educational ambition types identified in Section 3 across educational levels. We further subdivide the tertiary shares into Bachelor and Master/PhD as well as post-secondary fields of study. The final column reports the all shares for the entire population of couples as defined in Section 2.

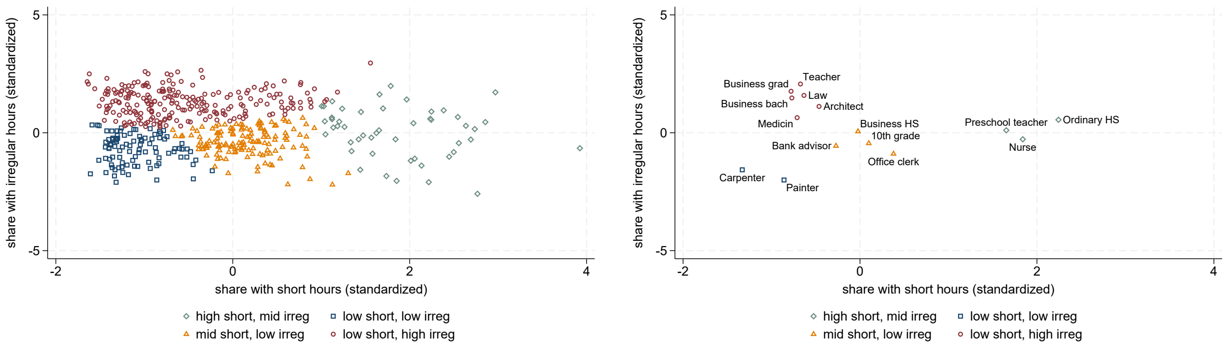
A.4 Clustering on Work Hours or Lifetime Income

This section presents the results for our alternative clustering approaches based on hours flexibility or lifetime earnings and compares them to the baseline ambition type classification.

Figure A.1: Educational Hours Flexibility types and their clustering variables

(a) All programs

(b) Examples

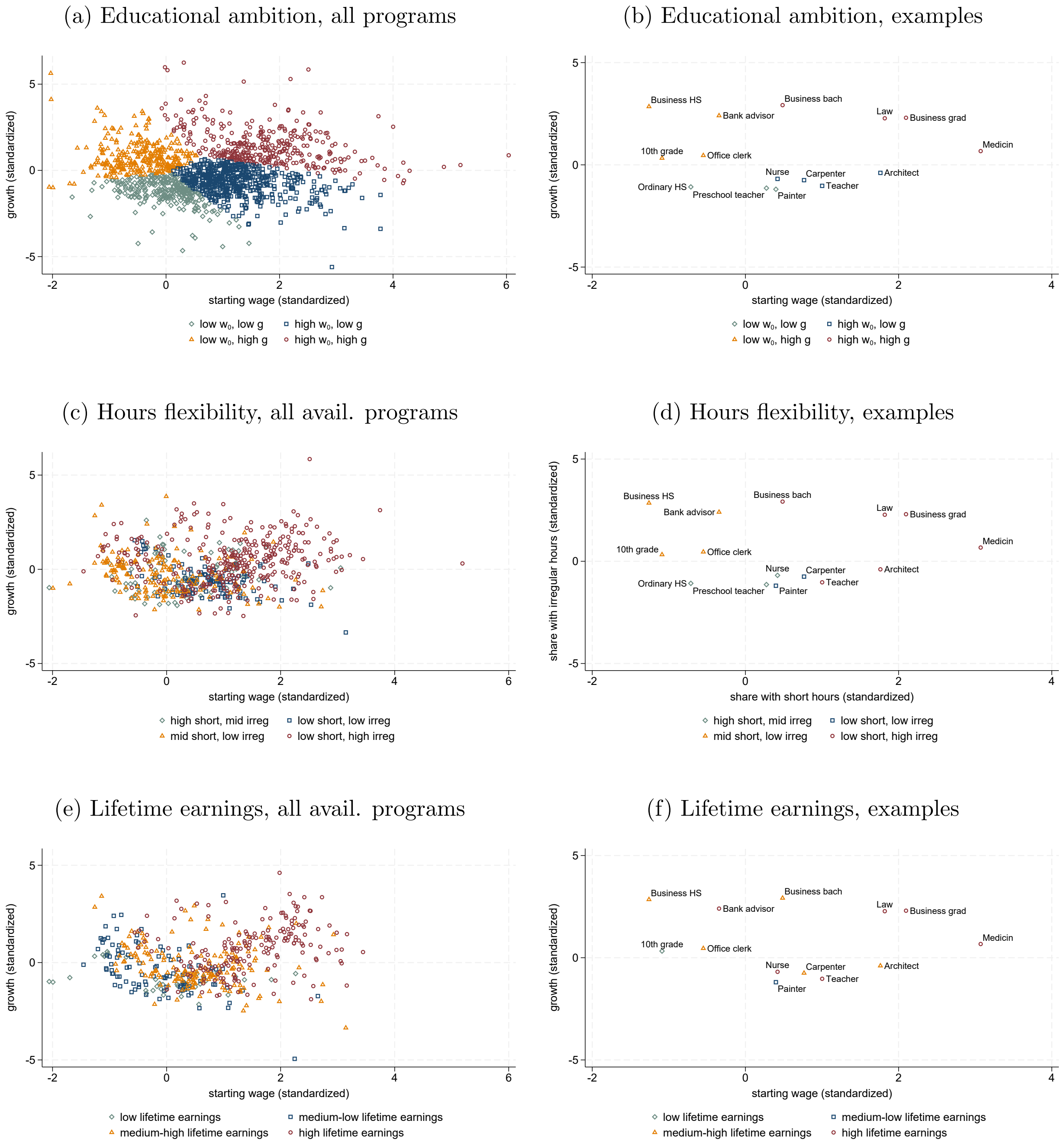


We start by presenting the results for clustering on the share of program graduates who work part-time and whose work schedule includes irregular hours. Panel (a) of Figure A.1 shows the resulting four clusters, while Panel (b) provides examples of programs in each cluster. The red-circle cluster consists of programs whose graduates typically have a low frequency of part-time work and a high frequency of irregular hours. Popular programs in this group include Business, Medicine, and Law. In contrast, the gray diamond cluster consists of programs whose graduates show a high frequency of short hours and have a lower prevalence of irregular hours. Examples include preschool teachers and nurses.

The classification based on lifetime earnings uses a one-dimensional k-means clustering approach and groups programs into low, medium-low, medium-high, and high income groups.

Comparison to Ambition Types In order to illustrate how the classifications based on lifetime earnings and hours flexibility relate to our baseline ambition-type classification, we compare all categorizations in the (w_0, g) plane in Figure A.2. Panel (a) shows the ambition-type clustering and can be compared to Panels (c) and (e) for hours-based and income-based types, respectively. In addition, Panels (b), (d), and (f) provide the types for the largest educational programs for each classification, respectively.

Figure A.2: Baseline vs. Hours-Flexibility and Lifetime-Earnings Types



Notes: The horizontal axis is w_0 (*standardized average starting wage*) and the vertical axis is g (*standardized average wage growth*)

For hours flexibility, we find substantial differences in particular for programs with low wage growth. Notably, the set of "inflexible" programs with low part-time share and high hours irregularity (low short, high irregular) also includes many programs with low wage growth, and not only programs with high wage level and growth (high w_0, high g). For example, the hours clustering groups teachers and architects in the same "inflexible" cluster that also contains lawyers and doctors. In contrast, the wage-based categorization treats teachers differently from lawyers because of their different wage dynamics, with teachers being similar to nurses and carpenters. Yet, the hours classification assigns these three programs into three different groups because of their differences in work schedules: nurses with a high part-time share, teachers with higher reported workloads at the evenings and weekends, and carpenters with the highest full-time share but regular schedules. These differences will turn out to be important in explaining differences in assortative matching and counterfactual inequality trends, as we discuss below.

For lifetime earnings (LE), the comparison shows that in particular low-low ambition types are spread across many different income groups. For this reason, the LE categorization cannot pick up increased assortative matching among low types. For high ambition types, we find more overlap with LE types but we note that some programs with substantially different wage profiles (e.g., nurse, teacher, business grad, lawyer) fall into the same, highest earnings group (compare Figure A.2 Panels (b) and (f)).

A.5 Wage dynamics predict career and family outcomes

To analyze these career patterns further, we use regression analysis at the program level and show in Table A.3 that the two building blocks of our ambition types—the wage measures w_0 and g capturing returns to human capital in the labor market —jointly explain key career and family outcomes, even when comparing graduates within the same education level or field of study. We further control for the measures of hours flexibility and life-time earnings, to probe the extent to which the wage measures capture the role of work schedules or total earnings, or reflect labor market returns whose influence on career and family outcomes cannot be fully captured by work hours or lifetime earnings.

To show this, we build on the literature and construct seven proxies for career and family outcomes of graduates of specific educational programs. The proxies emphasize the trade-off between career investments and time commitments to the family (Wiswall and Zafar, 2021; Goldin, 2014; Calvo et al., 2024). *Part-time penalty* is constructed as the ratio of the w_1 of full-time workers to that of part-time workers.[20] It reflects the additional return to working long hours, a measure of inflexiblilty inspired by Claudia Goldin's analysis of within-occupation gender differences in the US (Goldin, 2014). *Ever manager* is the fraction of graduates who reach a managerial position (hold a corresponding occupational code for at least two consecutive years). *Participation* captures the average share of time across the life-cycle during which program graduates are active in the labor market (work at least part-time). *Full-time* captures

[20]Recall that w_1 was the average wage in years 9-11 in the labor force used to construct the ambition types.

the fraction working at least 32 hours per week.[21] *Age at first child* is the average age among graduates at which the first child is born. *Wealth at age 50* is the average net wealth accumulated at age 50 in Danish Crowns (henceforth DKK).[22] Finally, *Lifetime earnings* is the sum of deflated annual earnings over 30 years after graduation.

The table shows the coefficients from regressions of the first six proxies (we control for life-time earnings in the fourth column of each Panel) on w_0 and g. The first column of each Panel includes educational-level fixed effects to compare programs within the same level. The second column instead uses fixed effects for field of education. The third and fourth column respectively combine level fixed effects with controls for lifetime earnings (col 3) or controls for the share of graduates working short hours and the share working irregular hours (col 4), as defined in Appendix A.2.

For all proxies, we find that higher starting wages or higher wage growth (and in most cases both) are associated with more career focus, which affects the work-life balance negatively. This is true even within the same levels or fields of study. For example, a one standard deviation change of wage growth (recall that w_0 and g are standardized) implies that the inflexibility measure (part-time penalty) increases by 2.1% *relative* to the mean across programs. Within the same level or field of education, the effects become somewhat smaller (1.9% and 1.5%, respectively) but remain highly significant.

Similarly, we find that higher starting wages and wage growth are associated with higher labor force participation and full-time work, as well as higher chances of manager promotion and higher net wealth, but also higher age at first child. Higher wage growth is associated with higher degrees of inflexibility (part-time penalty) across all specifications, while starting wages are less so. This is expected as wage growth is most likely associated with higher degrees of investment in human capital. Finally, age at first child is strongly associated with starting wages and wage growth in all specifications except when controlling for life-time earnings where the association with wage growth disappears. All these patterns emphasize important heterogeneity in labor market and family outcomes across programs that our ambition types can capture within educational levels and fields.

Moreover, the third specification in each model shows that starting wages and wage growth correlate with our measures of work-life balance even conditional on discounted lifetime earnings. The main takeaway from this result is that collapsing the multi-dimensional labor market trajectories of individuals into a one-dimensional measure of earnings misses the interplay be-

[21]Based on the RAS register. Before 2008 the threshold between part-time and full-time is at 30 hours (1980 to 1992) or 27 hours (1993 to 2007), see Lund and Vejlin (2016).

[22]Net wealth excludes assets in pension funds and is deflated with 2000 as the base year.

Table A.3: The Work-Life Balance of Ambition beyond Levels, Fields, and Lifetime Earnings

FE model: *Controls:*	Levels *None*	Fields *None*	Levels *Earnings*	Levels *Hours*	Levels *None*	Fields *None*	Levels *Earnings*	Levels *Hours*
	(a) Part-time penalty				(b) Ever manager			
w_0	0.0072	0.0030	0.0294	-0.0105	0.0241	0.0127	0.0227	0.0144
	(0.007)	(0.005)	(0.006)	(0.010)	(0.005)	(0.005)	(0.007)	(0.006)
g	0.0208	0.0160	0.0323	0.0136	0.0262	0.0190	0.0294	0.0214
	(0.005)	(0.005)	(0.005)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)
Mean	1.098				0.051			
Obs.	985	985	443	684	1,874	1,874	496	697
Adj. R^2	0.316	0.480	0.450	0.373	0.409	0.467	0.450	0.529
	(c) Participation				(d) Full time work			
w_0	0.0377	0.0278	-0.0143	0.0288	0.0955	0.0844	0.0703	0.0201
	(0.009)	(0.014)	(0.008)	(0.013)	(0.013)	(0.016)	(0.009)	(0.011)
g	0.0366	0.0352	0.0151	0.0342	0.0212	0.0194	0.0131	-0.003
	(0.007)	(0.009)	(0.007)	(0.008)	(0.008)	(0.011)	(0.006)	(0.005)
Mean	0.764				0.821			
Obs.	1,874	1,874	496	697	1,874	1,874	496	697
Adj. R^2	0.449	0.466	0.664	0.471	0.314	0.293	0.494	0.560
	(e) Age at first child				(f) Wealth at age 50			
w_0	0.529	0.561	0.153	0.414	0.144	0.134	0.135	0.105
	(0.366)	(0.366)	(0.460)	(0.455)	(0.016)	(0.016)	(0.016)	(0.017)
g	0.277	0.339	0.0269	0.154	0.0945	0.0864	0.0858	0.0777
	(0.185)	(0.218)	(0.190)	(0.203)	(0.013)	(0.015)	(0.013)	(0.014)
Mean	31.61				0.243M			
Obs.	1,824	1,824	493	692	1,305	1,305	496	647
Adj. R^2	0.012	0.015	0.143	0.021	0.465	0.472	0.539	0.479

Notes: *FE* stands for *fixed effects*, *Obs.* for *observations*, and *Adj.* for *adjusted.* w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. *Earnings* stands for *Life-time earnings* as defined in the text of this section. Each panel (a) to (f) shows the coefficients on w_0 and g in a regression of the work-life balance proxy (defined in the text of this section), which includes the fixed effects and controls as indicated in the columns' labels. Robust standard errors in parentheses.

tween labor market starting conditions and growth trajectories. Different combinations of starting wages and wage growth can have opposite implications for work-life balance. Consider that the same level of lifetime earnings can be reached through a high starting wage and relatively low growth, or a low starting wage and relatively high growth. Indistinguishable by means of lifetime outcomes, these different combinations imply, e.g., different working hours. Thus, they have different values from the perspective of marriage and family, which is captured by different ambition types. Capturing this heterogeneity in the family value of different career types is a key advantage of our new categorization.

Finally, we find in the fourth column of each panel that ambition types strongly predict career outcomes and correlate with work-life balance outcomes in part through labor-supply patterns. Compared to the previous regression models, the coefficients on our wage moments decline somewhat in absolute value for several of the career and family outcomes when controlling for the share of workers with short or irregular hours. While the wage moments typically remain statistically significant, the hours moments are also significantly related to the family and career outcome measures. As such, the results confirm the notion that labor market returns imply opportunity costs for the family and lead to different labor supply choices.

A.6 Weights for the Aggregate Measure of Assortative Matching

Almar and Schulz (2024) derive a decision rule to minimize the distortion of likelihood-ratio-based measures due to changing marginal distributions. While accounting for changing population shares ensures proper scaling of the likelihood ratios (see equation (1)), the marginal distributions also influence the measure beyond this desired feature. To minimize this distortion, Almar and Schulz (2024) propose to set λ in equation (3) such that the combined distortion from changing male and female marginal distributions is minimized. In our data, the educational attainment of females was initially lower but increased relatively more compared to males. Thus, to the minimize the distortion, it is optimal to put the weight on the "short side" of the market (high-type females). Recall that λ $(1-\lambda)$ is the parameter of the male (female) marginal in the convex combination, and let γ_1 (γ_2) be the total distortional effect for men (women) in the total differential of the aggregate measure (2). The optimal λ is

$$\lambda^* = \begin{cases} 0 & \text{if} \quad \text{sign}(\gamma_1) = \text{sign}(\gamma_2), \quad |\gamma_2| > |\gamma_1| \\ \frac{\gamma_1}{\gamma_1 - \gamma_2} & \text{if} \quad \text{sign}(\gamma_1) \neq \text{sign}(\gamma_2) \\ 1 & \text{if} \quad \text{sign}(\gamma_1) = \text{sign}(\gamma_2), \quad |\gamma_1| > |\gamma_2|. \end{cases} \tag{A.1}$$

Intuitively, if the signs of the total distortional effect are similar for men and women (e.g., the share of "high-type" individuals could be increasing for both genders), the weight is set such that the bigger change (in absolute terms) is taken into account by the aggregate measure. For example, if $\gamma_2 > \gamma_1$, female type distribution changes are relatively more important. To reflect this, changes of the male marginal distribution are taken out by setting λ equal to 0. The female marginal distribution cancels out in the likelihood ratios (1), removing its distortional impact. For the intermediate case $\text{sign}(\gamma_1) \neq \text{sign}(\gamma_2)$, $\lambda \in (0,1)$ ensures that both population share changes are reflected. The optimal λ^* may change over time, depending on the changing configuration of the marginals. Thus, the optimal weights may flip when, e.g., the population share of high-type women becomes greater than the population share of high-type men. To ensure that trends in assortative matching are comparable over time, we set λ to the modal value suggested by (A.1) over time. In the vast majority of years and for all categorizations, the rule suggests putting the weights on female type distribution changes.

A.7 Counterfactual Scenarios and Assortative Matching

In this appendix section, we provide the formal derivation of the result that our choice of weights in Section 5.1, scenario (i), fixed household composition, guarantees that those who are married in year τ exhibit the same degree of assortative matching S as the 1980 households. In addition, the log odds ratios are also held fixed at their 1980 values.

To see this result, first note that our choice of weights for $\tau_y = \tau$ and $\tau_\mu = 1980$ is

$$\widehat{\psi}_{\tau,80}(i,j) \;=\; \frac{\frac{N_{80}(i,j)}{N^{\text{all}}_{80}}}{\frac{N_\tau(i,j)}{N^{\text{all}}_{\tau}}} \;=\; \frac{N_{80}(i,j)}{N_\tau(i,j)} \times \frac{N^{\text{all}}_{\tau}}{N^{\text{all}}_{80}} = \frac{P^M_{80}(i,j)}{P^M_\tau(i,j)} \times \underbrace{\frac{\sum_{r\neq\phi}\sum_{s\neq\phi} N_{80}(r,s)}{\sum_{r\neq\phi}\sum_{s\neq\phi} N_{\tau}(r,s)} \times \frac{N^{\text{all}}_{\tau}}{N^{\text{all}}_{80}}}_{:=A},$$

where $N_y(i,j)$ denotes the number of $(t_m = i, t_f = j)$ households (including singles if one of the types is $\emptyset$) and N^{all}_y is the total number of households in year y, while $P^M_y(i,j)$ denotes the fraction of married couples of type $(t_m = i, t_f = j)$ in year y.

Using equations (1) and (3) to write the aggregate measure S in equation (2) explicitly, and applying the weights $\widehat{\psi}_{\tau,80}(i,j)$, yields the proposed result that $\widetilde{S}_\tau = S_{80}$:

$$\begin{aligned}
\widetilde{S}_\tau &= \sum_{t=1}^{T} \frac{P^M_\tau(t,t)\times\widehat{\psi}_{\tau,80}(t,t)}{\left(\sum_{s=1}^{T} P^M_\tau(t,s)\times\widehat{\psi}_{\tau,80}(t,s)\right)\left(\sum_{r=1}^{T} P^M_\tau(r,t)\times\widehat{\psi}_{\tau,80}(r,t)\right)} \\
&\qquad \times \left(\lambda\sum_{s=1}^{T} P^M_\tau(t,s)\times\widehat{\psi}_{\tau,80}(t,s) \;+\; (1-\lambda)\sum_{r=1}^{T} P^M_\tau(r,t)\times\widehat{\psi}_{\tau,80}(r,t)\right) \\
&= \sum_{t=1}^{T} \frac{P^M_\tau(t,t)\;\times\;\frac{P^M_{80}(t,t)}{P^M_\tau(t,t)}\;\times\;A}{\left(\sum_{s=1}^{T} P^M_\tau(t,s)\;\times\;\frac{P^M_{80}(t,s)}{P^M_\tau(t,s)}\;\times\;A\right)\left(\sum_{r=1}^{T} P^M_\tau(r,t)\;\times\;\frac{P^M_{80}(r,t)}{P^M_\tau(r,t)}\;\times\;A\right)} \\
&\qquad \times \left(\lambda\Big(\sum_{s=1}^{T} P^M_\tau(t,s)\;\times\;\frac{P^M_{80}(t,s)}{P^M_\tau(t,s)}\;\times\;A\Big) \;+\; (1-\lambda)\Big(\sum_{r=1}^{T} P^M_\tau(r,t)\;\times\;\frac{P^M_{80}(r,t)}{P^M_\tau(r,t)}\;\times\;A\Big)\right) \\
&= S_{80}\;\times\;\frac{A\;\times\;A}{A^2} \;=\; S_{80}
\end{aligned}$$

By a similar argument, we can show that the log odds ratios remain fixed. Consider types $i = \{t(1), ..., t(T-1)\}$ and $j = \{t(2), ..., t(T)\}$ for any categorization t. For any 2×2 submatrix of joint types in which $i \neq j$,

$$\begin{aligned}\widetilde{I}_{\text{odds},\tau} &= \log\left(\frac{P_\tau^M(i,i)\ \times\ \widehat{\psi}_{\tau,80}(i,i)\ \times\ P_\tau^M(j,j)\ \times\ \widehat{\psi}_{\tau,80}(j,j)}{P_\tau^M(j,i)\ \times\ \widehat{\psi}_{\tau,80}(j,i)\ \times\ P_\tau^M(i,j)\ \times\ \widehat{\psi}_{\tau,80}(i,j)}\right)\\ &= \log\left(\frac{P_{80}^M(i,i)\ \times\ P_{80}^M(j,j)}{P_{80}^M(j,i)\ \times\ P_{80}^M(i,j)}\right) = I_{\text{odds},80}\end{aligned}$$

B Additional Results

B.1 Differences in Demographic Changes Across Categorizations

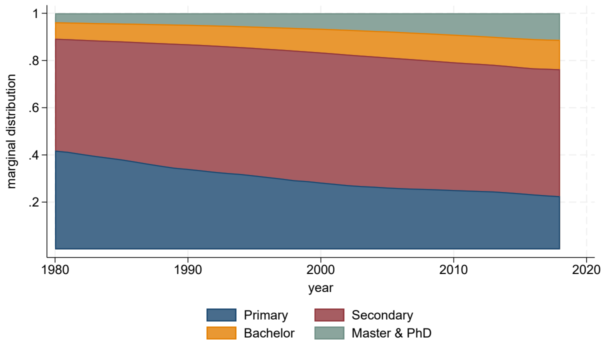
B.1.1 Trends in Education Distributions

How we view educational attainment and its evolution differs depending on which categorization we consider. Figure B.1 shows the fraction of men (left panels) and women (right panels) by education type and year, for our three definitions of education—Level in panels (a) and (b), Ambition in (c) and (d), and Fields in (e) and (f). Comparing the distribution of education levels and ambition types, we first note that for educational levels, the "secondary" category is large and relatively stable for both men and women, while the most frequent ambition types for both men and women are the ones that group education programs with high wage growth. Notably, while over time we observe an increasing representation of individuals, especially women, in Bachelor or more education levels relative to Primary education, we observe an increasing representation of the population in both the low wage growth and the highest ambition types.

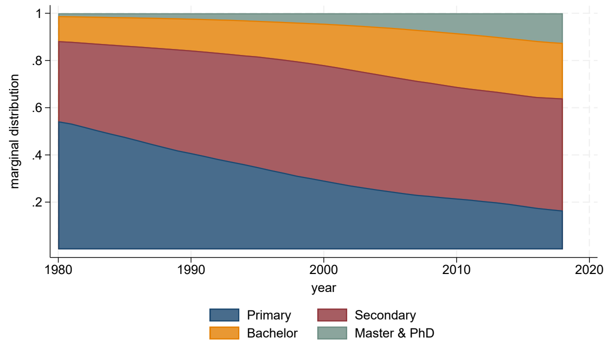
In addition, Figure B.2 shows the educational composition of married individuals over time. We observe that the composition of married individuals has shifted over time towards highly-educated (Master & PhD for both genders and also Bachelor degrees for women) and highly ambitious individuals (especially for women), but there are important differences across categorizations and gender. For example, based on ambition we also observe an increasing representation of low-ambition individuals among the married population.

Figure B.1: Marginal Type Distributions

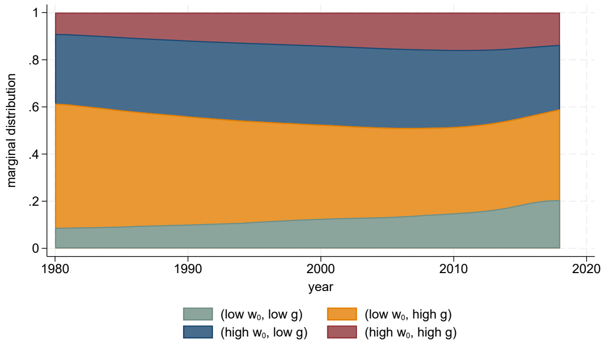
(a) Educational Level, Men



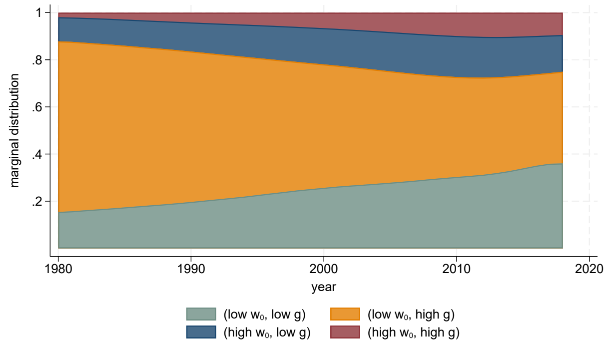
(b) Educational Level, Women



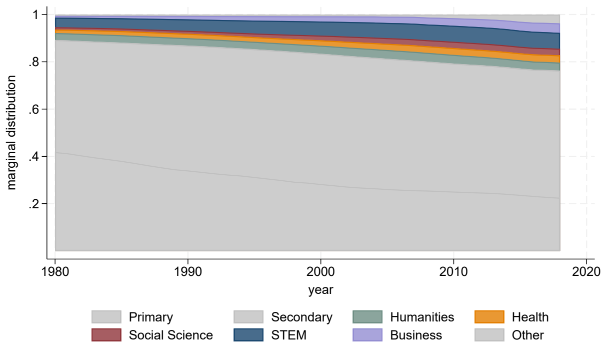
(c) Educational Ambition, Men



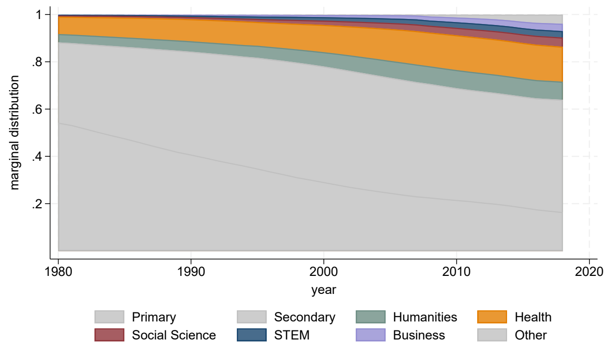
(d) Educational Ambition, Women



(e) Educational Fields, Men



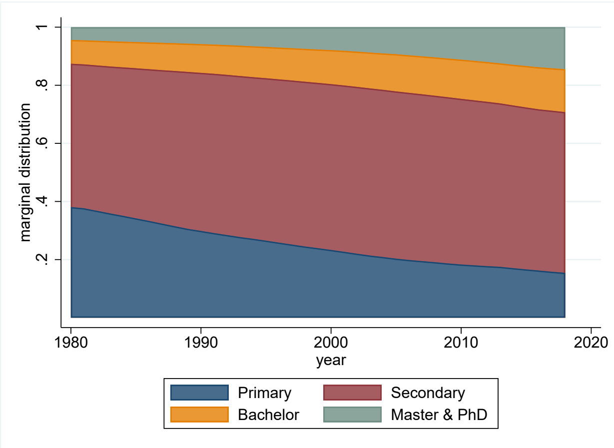
(f) Educational Fields, Women



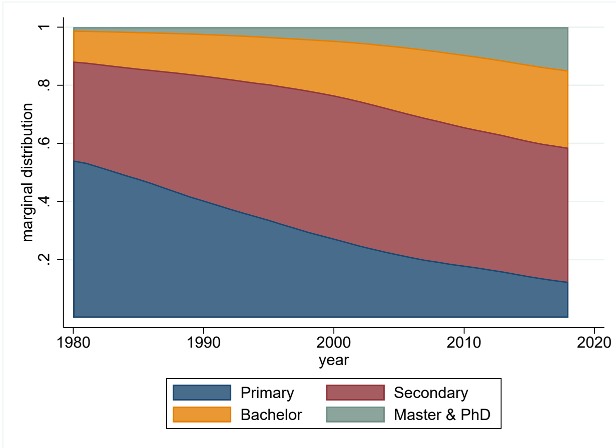
Notes: Marginal distributions for men and women over time by educational level and educational ambition. Sections 2 and 3 explain how the sample, educational levels, educational- fields and the labor market outcome (residualized log hourly wages) underlying the educational ambition types are constructed.

Figure B.2: Marginal Type Distributions, Conditional on Marriage

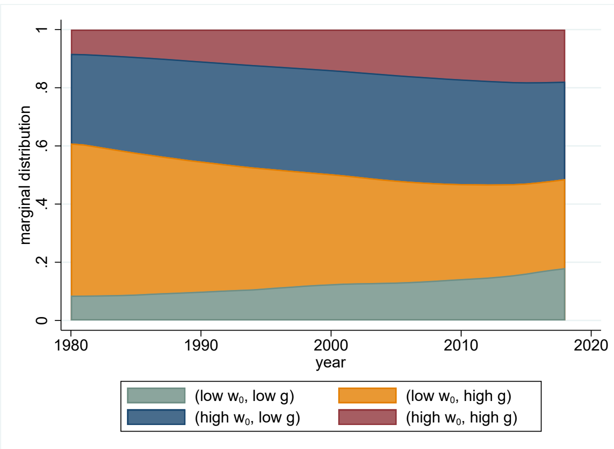
(a) Educational Level, Married Men



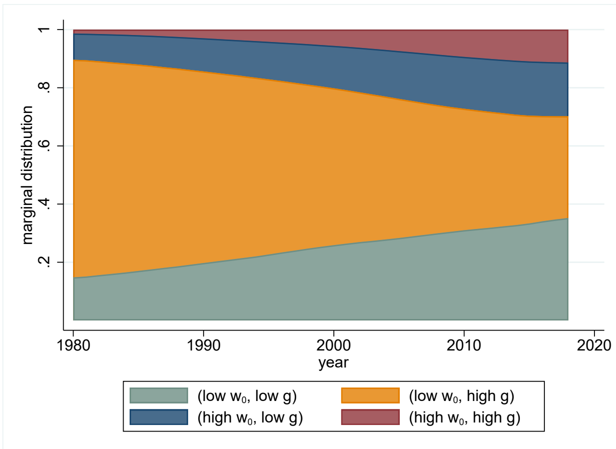
(b) Educational Level, Married Women



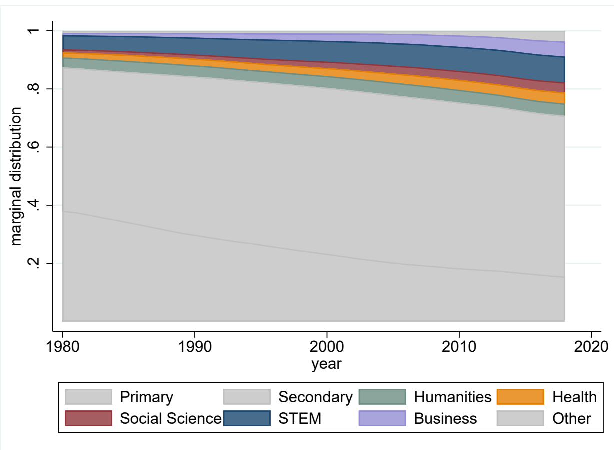
(c) Educational Ambition, Married Men



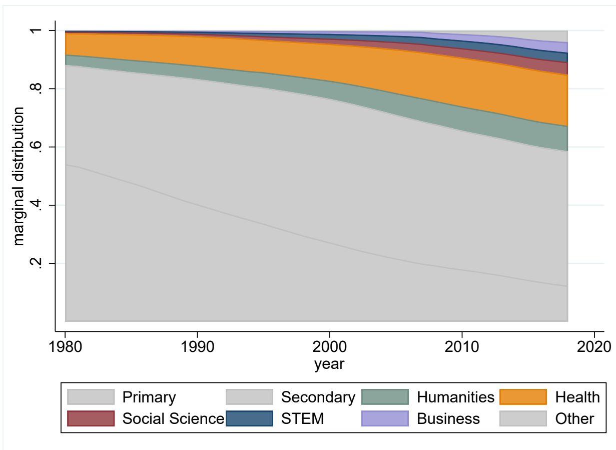
(d) Educational Ambition, Married Women



(e) Educational Fields, Married Men



(f) Educational Fields, Married Women

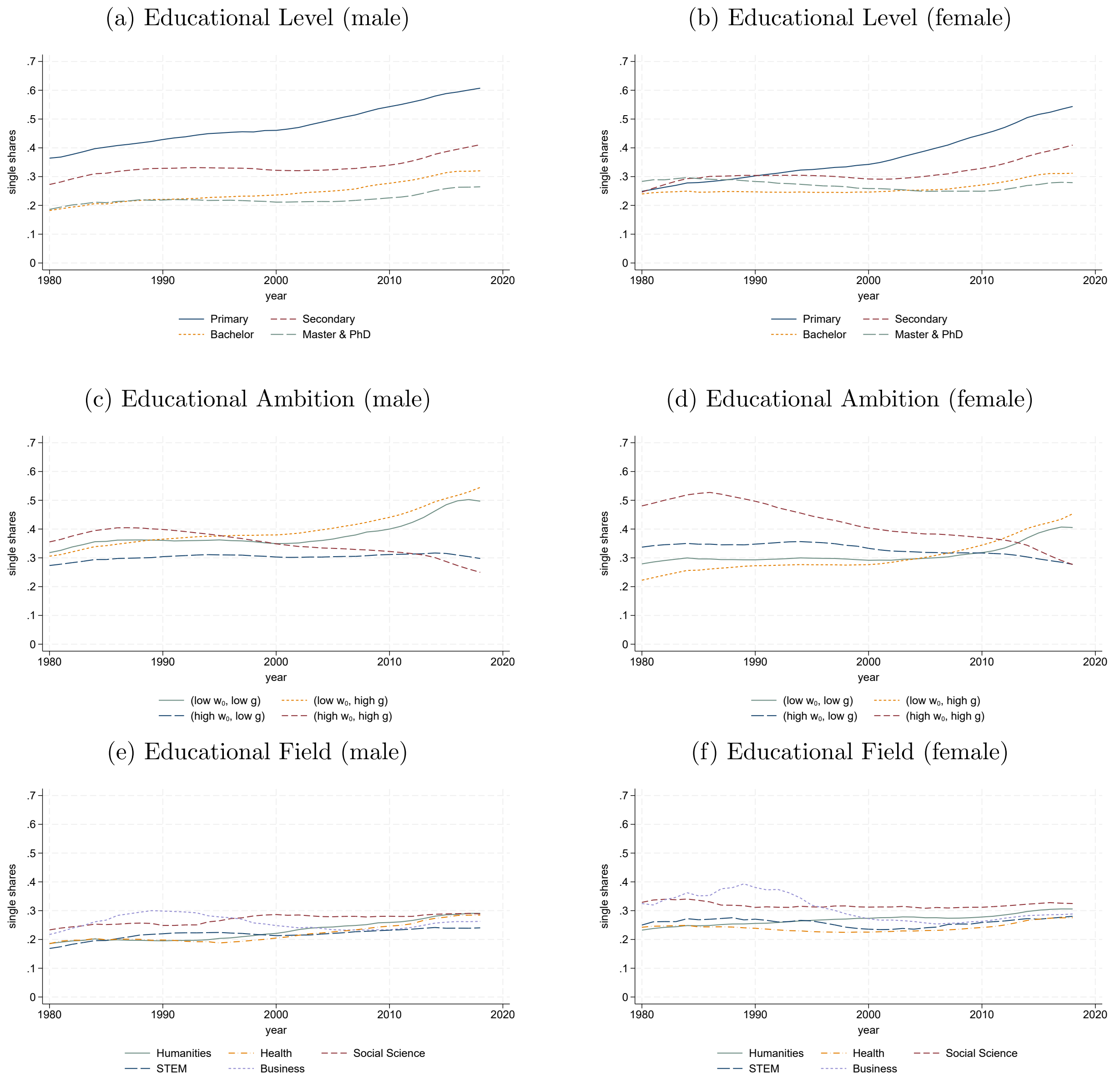


Notes: Marginal distributions for married and cohabiting men and women over time by educational level, educational ambition, and educational field. Sections 2 and 3 explain how the sample, educational levels, educational- fields and the labor market outcome (residualized log hourly wages) underlying the educational ambition types are constructed.

B.1.2 Trends in Marriage

We analyze how individuals sort into being married or single based on their education type and make comparisons across categorizations. In Figure B.3, we show how single shares of men and women have evolved for all the types included in our educational-level, educational-ambition, and educational-field categorizations.

Figure B.3: Single Shares for Educational-Level, Ambition Types, and Fields of Study



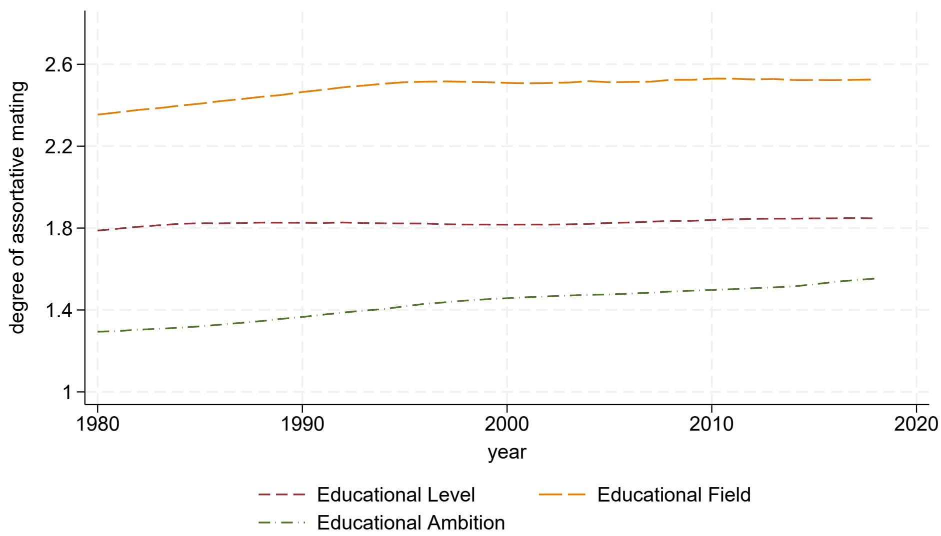
Notes: Single shares by gender for all for types of the educational level (Panels a and b), educational ambition (Panels c and d), and educational field (Panels e and f) categorizations. Types are constructed as explained in Section 3.

For educational-level types, single shares have increased for all types for both men and women, and most significantly so for individuals with primary education (blue solid lines in Panels (a) and (b), Figure B.3). In contrast, if we interpret the data through the lens of our novel ambition types, single shares did not increase for all types. Specifically, men and women who graduate from ambitious educational programs with high starting wages and high wage growth (red dashed lines) exhibit falling single shares. This is especially pronounced for high-type women, who had the highest probability of remaining single in 1980, when their single share was close to 50%. It decreased to around 30% in 2018. If more women with high earnings potential enter marriage, inequality between households might increase, depending on the partner type and couples' labor supply choices.

Single shares increased for both men and women who graduate from educational programs with low starting wages (gray solid and yellow short-dashed lines). The blue dashed lines—the single shares of men and women who hold degrees with high starting wage but low wage growth—changed relatively little but decreased slightly for women. These striking differences in single share trends across categorizations show that the ambition types reveal fundamental changes in marriage market matching that remain undetected using standard educational-level types and potentially matter for inequality trends.[23]

B.2 Trends in Measures of Assortative Matching

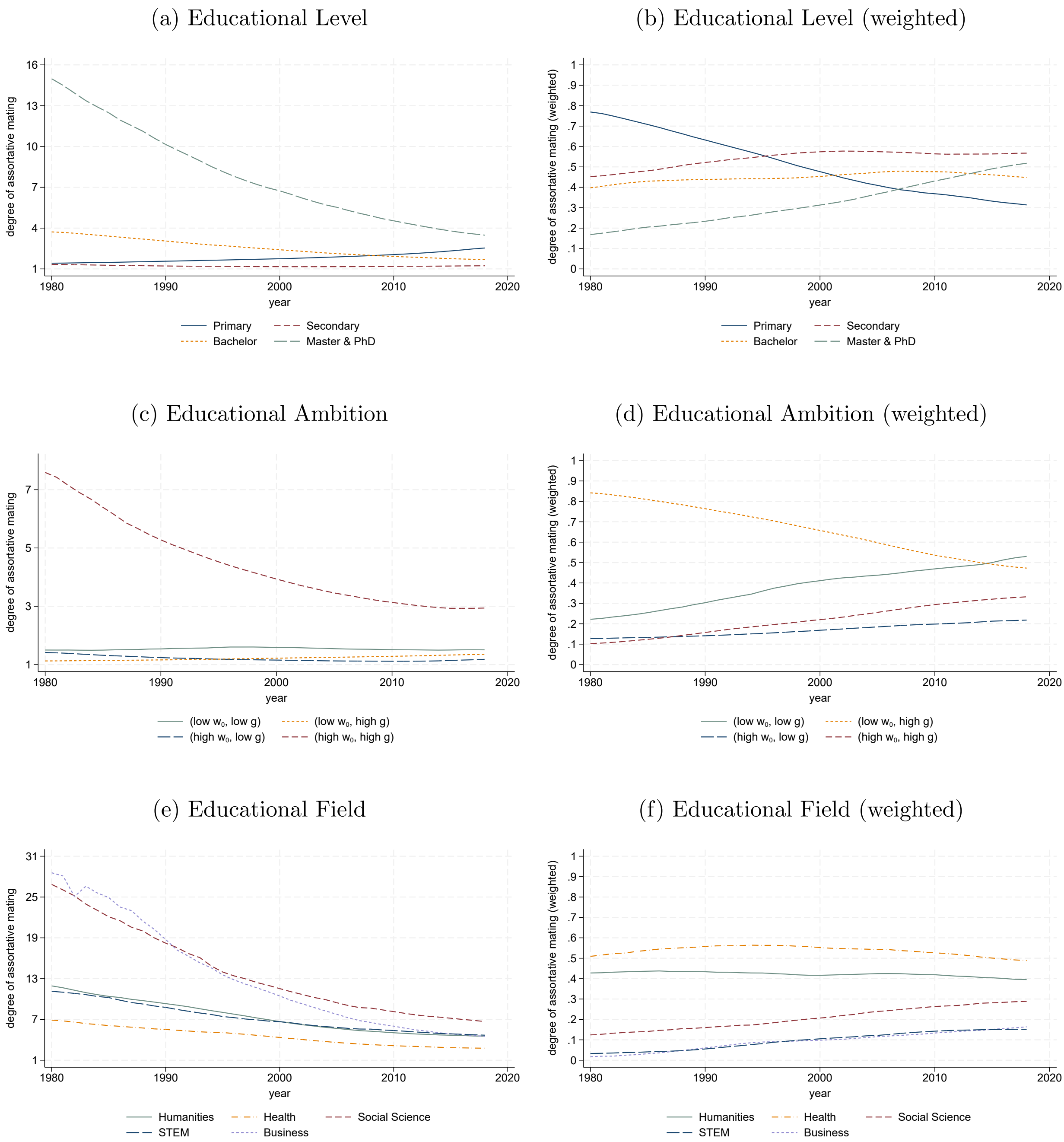
Figure B.4: Aggregate Measures in Levels



Notes: The figure shows the measure $\mathcal{S}$ derived in Section 4, equation (2) for educational level types (red short-dashed line), educational field types (orange long-dashed line) and educational ambition types (green dash-dotted line). Types are constructed as explained in Section 3.2.

[23]The single-share trends by educational field are rather flat, see Panels (e) and (f). They are different from both educational levels and ambition, which underscores our point that the role that the extensive margin plays depends on the categorization.

Figure B.5: Type-specific Likelihood Indices, unweighted and weighted



Notes: Likelihood indices for equal-education couples (equation (1)) for educational level, educational ambition, and educational field categorizations. Types are constructed as explained in Section 3.2.

B.3 Work Hours and Lifetime Earnings

In this section, we compare our main results for assortative matching and inequality trends based on our ambition type classification to analogous results for the classifications based on work hours (abstracting from the returns to work hours and schedules) or lifetime earnings (abstracting from different career trajectories that lead to similar total income).

Yet, we note that both approaches come with significant measurement challenges. To con-

Table B.1: Assortative Matching and Fixed Household Composition for Hours-based and Lifetime-Earnings-based Classifications

	(a)		(b)			(c)		(d)	
	N (1,000s)		Assortative Matching			Gini, data		Gini, (i)	$\frac{\Delta_{Gini,(i)}}{\Delta_{Gini,data}}$
	1980	2018	1980	2018	Change	1980	2018	2018	
Ambition types	2,427	2,801	1.29	1.55	20.1%	0.298	0.400	0.364	64.6%
(i) Work hours and flexibility									
Hours flexibility	2,311	2,657	1.53	1.61	5.0%	0.298	0.401	0.367	66.8%
Ambition, hours sample	2,311	2,657	1.31	1.57	19.1%	0.298	0.401	0.363	63.0%
(ii) Lifetime earnings sample 1990 – 2010									
	1990	2010	1990	2010	Change	1990	2010	2010	
Lifetime earnings	1,555	1,578	1.52	1.56	3.0%	0.332	0.353	0.344	57.1%
Ambition, LE sample	1,555	1,578	1.40	1.55	11.0%	0.332	0.353	0.345	64.7%
Ambition, full sample	2,676	2,705	1.37	1.50	9.7%	0.327	0.363	0.347	55.4%

Notes: Columns (a) display the number of observations in each case in thousands of individuals for both 1980 and 2018. Columns (b) show our measure of assortative matching $\mathcal{S}$ derived in Section 4 for both years along with the percentage change. Columns (c) show the observed Gini coefficients in each case for 1980 and 2018. Columns (d) show the counterfactual Gini coefficient in the fixed marriage market scenario (i), i.e., had the composition of households stayed fixed at its 1980 level in each case and the fraction of the observed change in Gini that is captured by the change in the counterfactual scenario, $\Delta_{Gini,(i)}/\Delta_{Gini,data}$. Each row shows the columns' statistic for one of the alternative definitions of ambition types.

struct hours types, we rely on survey responses from the LFS, which represent a small fraction of all workers in Denmark. We decide to include all programs with at least 50 survey responses in our analysis. The LFS is limited to 2000–2018, and we impute the hours type to the earlier part of the sample for each program, assuming stable hours characteristics.

To construct lifetime earnings, we need to observe program graduates for at least 30 years from the time of graduation. This leads to lower sample coverage of this alternative classification in early and late years of our analysis period, when a higher share of individuals have outdated or new degrees with missing information on lifetime earnings, respectively. This limitation affects couples more than singles because our analysis requires assigning types to both spouses to be included. As a result, we focus on a shorter time period from 1990 to 2010 for this robustness analysis because over this period the share of singles and couples covered by the lifetime-earnings classification is highest and stable. To interpret the magnitude of the results based on the lifetime-earnings classification, we also provide results for our benchmark ambition type classification for the 1990–2010 period. Specifically, we report results both for the smaller sample of households included in the lifetime-earnings analysis and for the full sample of households in these years.

B.3.1 Assortative Matching

Table B.1 present the results for hours in Panel (i) and lifetime earnings in Panel (ii), respectively.

We start by analyzing the trends in assortative matching implied by each classification. For both alternatives, we find that the increase in PAM is much smaller than for our ambition types. Overall, this suggests that the increase we find is driven by returns to human capital. This cannot be detected by our lifetime earnings measure, and it is not consistent with an increase in the importance of work-life balance as captured by our hours flexibility measures.

First, while assortative matching on hours is positive (the aggregate measure is above one), the hours-based classification indicates only a small increase in PAM over time. As illustrated in Appendix A.4, there is a close relationship between wage dynamics and hours flexibility of different educational programs. Yet, the hours-based classification focuses on the number of hours and their irregularity, not on their returns. This distinction is salient in Figure A.2 where the hours classification treat teachers and lawyers the same because of similar hours profiles, but they fall into different ambition types because of the different wage dynamics. These differences matter because the substantial increase in positive assortative matching based on ambition types is partly driven by programs with the highest career potential.

Second, Panel (ii) shows similar results for lifetime earnings, thus abstracting from the heterogeneity in starting wages and wage growth conditional on lifetime earnings: we find only a small increase in AM by about 3% over 1990–2010 based on lifetime-earnings types. This analysis includes about 58% of the sample in both 1990 and 2010, with similar coverage of singles and couples. In contrast, the increase implied by our benchmark types is much larger, at 11% in the same sample, or 9.7% in the full sample over this period, amounting to about half of the total increase in AM that we measure over four decades in the main results (20.1%).

B.3.2 Inequality

Turning to inequality trends in columns (c) and (d) of Table B.1, we find that both hours-based and lifetime-earnings types can capture a similarly large role of the household composition in inequality trends. Specifically, we find similar reductions in the counterfactual Gini coefficient when holding the composition fixed with these alternative categorizations.

The similar role of household composition in overall inequality trends implied by both wage-based and hours-based classifications is consistent with their overlap and the role of both career and family objectives in marital sorting. Since we observe less pronounced trends in assortative matching based on hours or lifetime earnings, it is plausible that changes in the composition of households are more pronounced for different-type couples when using the hours-based and lifetime-earnings-based classifications.

For hours, these changes in off-diagonal couple types, in turn, suggest changing patterns of hours specialization. Specifically, increased PAM by ambition happens in two ways that cancel each other out in the aggregate measure for hours: (i) by increasing the share of couples with same ambition and similar hours schedules (e.g., lawyer-lawyer couples) but also (ii) by increasing the share of couples with similar wage dynamics and different schedules (e.g., nurse-carpenter or teacher-nurse couples).

B.4 Counterfactual Scenarios (ii) and (iii) based on Gutierrez (2020)

Table B.2: Scenarios (ii) and (iii) using the Gutierrez (2020) version of Choo and Siow (2006)

	(a) Gini		(b) $P90/P50$		(c) $P50/P10$	
Factual change (Δ_{Data})	0.102	100%	0.322	100%	3.626	100%
	Δ_{Gini}	$\frac{\Delta_{Gini}}{\Delta_{Data}}$	$\Delta_{P90/P50}$	$\frac{\Delta_{P90/P50}}{\Delta_{Data}}$	$\Delta_{P50/P10}$	$\frac{\Delta_{P50/P10}}{\Delta_{Data}}$
(ii) Fixed marital surplus						
Educational Level	0.074	73%	0.213	66%	2.263	62%
Educational Field	0.074	73%	0.215	67%	2.207	61%
Educational Ambition	0.069	68%	0.185	58%	2.148	59%
(iii) Fixed marginals						
Educational Level	0.124	122%	0.424	131%	6.020	166%
Educational Field	0.121	119%	0.410	127%	6.011	166%
Educational Ambition	0.102	100%	0.303	94%	4.518	125%
(iii.a) Fixed marginals (male)						
Educational Level	0.101	99%	0.299	93%	4.266	118%
Educational Field	0.100	98%	0.295	92%	4.281	118%
Educational Ambition	0.098	97%	0.298	93%	3.870	107%
(iii.b) Fixed marginals (female)						
Educational Level	0.122	120%	0.392	122%	5.231	144%
Educational Field	0.121	119%	0.392	122%	5.234	144%
Educational Ambition	0.105	103%	0.323	100%	4.201	116%

Notes: Panels show the counterfactual scenarios constructed as explained in Section 5.2 (panels (ii) to (iii.b)). We modify the Choo and Siow (2006) model following Gutierrez (2020) and do not assume independence of irrelevant alternatives. $P90/P50$ ($P50/P10$) is the ratio of the 90th and 50th (10th) percentile in the income distribution. Δ_{Data} shows the observed inequality changes. $\Delta_{Gini}/\Delta_{Data}$ is the counterfactual change relative to the observed change. Each row within each scenario shows the columns' statistic for one of the three definitions of types (as explained in Section 3): educational level, educational field, and educational ambition types.

B.5 Details on Robustness

B.5.1 Alternative Construction of Ambition Types

In this section, we assess whether our main results are sensitive to constructing ambition types in alternative ways. Using the notation from the conceptual framework in Section 3.1, recall that our benchmark categorization creates four types using information at the level of the educational program i, the sub-vector of characteristics $\tilde{x}_i = (w_{0i}, g_i)$, and the k-means mapping algorithm $\mathcal{T}_{Ambition}(\tilde{x})$. Table B.3 shows the trends in the degree of assortative matching (analyzed in Section 4) and the inequality contributions in the fixed household composition counterfactual scenario (analyzed in Section 5, scenario (i)) that we find when constructing the ambition types in various alternative ways. For convenience, the first row repeats the results for our benchmark categorization of ambition types. The columns show: (a) the the numbers of observations in 1980 and 2018, (b) the change in our measure of PAM, equation (2), between those years, (c) the observed Gini coefficients in 1980 and 2018, and (d) the counterfactual Gini in the fixed household composition scenario, along with the explained share relative to the trend in the data.

In Panel (i), we analyze the sensitivity of our findings with respect to the assumption that the ambition types do not vary by gender or over time. In the row labeled *Types by gender*, we consider the possibility that education programs may send different signals depending on the gender of the graduate. That is, we construct the four ambition types separately for women and men by using information at the program-gender level i. Formally, we consider the sub-vector of characteristics $\tilde{x}_i^f = (w_{0i}^f, g_i^f)$ for women and $\tilde{x}_i^m = (w_{0i}^m, g_i^m)$ for men and create female and male ambition types through k-means mappings $\mathcal{T}_{Ambition}(\tilde{x}^f)$ and $\mathcal{T}_{Ambition}(\tilde{x}^m)$, respectively. Online Appendix Figure B.6 (which has the same structure as Figure 1) shows that our method successfully generates four types clearly distinct in terms of labor market prospects (as is the case for our benchmark). Even though most of the biggest programs are assigned to the same ambition type for men and women, there are exceptions. For example, architecture is a program associated with a high wage growth type for women but a low wage growth type for men. We find that the degree of assortative matching based on gendered ambition types increased slightly less than in our benchmark (18.6%, which is still significantly more than AM by levels or fields) and that the composition of couples explains slightly less of the changes in inequality than our benchmark does (almost 30%, which is significantly more than what we find using levels or fields).

Similarly, for the row labeled *Types by cohort*, we construct ambition types by cohorts of

Table B.3: Assortative Matching and Fixed Household Composition with Alternative Ambition Types

	(a) N (1,000s) 1980	2018	(b) Assortative Matching 1980	2018	Change	(c) Gini, data 1980	2018	(d) Gini, (i) 2018	$\frac{\Delta_{Gini,(i)}}{\Delta_{Gini,data}}$
Benchmark types									
Labor income	2,427	2,801	1.29	1.55	20.1%	0.298	0.400	0.364	64.6%
Disposable income	2,427	2,801	1.29	1.55	20.1%	0.227	0.366	0.327	72.3%
(i) Gender- and cohort-specific ambition types									
Types by gender	2,426	2,798	1.15	1.37	18.6%	0.298	0.400	0.374	74.3%
Types by cohort	2,408	2,799	1.34	1.58	18.2%	0.298	0.400	0.372	72.7%
(ii) Different numbers of clusters									
Three ambition types	2,427	2,801	1.23	1.42	15.2%	0.298	0.400	0.373	73.2%
Five ambition types	2,427	2,801	1.39	1.73	24.9%	0.298	0.400	0.361	61.5%
(iii) Different clustering variables									
Only g	2,427	2,801	1.27	1.40	9.9%	0.298	0.400	0.375	75.6%
Only w_0	2,427	2,801	1.35	1.56	15.7%	0.298	0.400	0.375	75.4%
Male w_0, g	1,191	2,775	1.40	1.60	14.2%	0.319	0.401	0.365	56.7%
w_0, part-time penalty	2,345	2,725	1.37	1.50	9.2%	0.298	0.401	0.369	69.2%
w_0, manager premium	2,417	2,360	1.46	1.91	31.4%	0.298	0.378	0.354	70.4%
(iv) Different level of aggregation									
Programs × univ.	2,409	2,795	1.28	1.55	20.7%	0.297	0.400	0.364	65.2%
Sub-fields × levels	2,427	2,642	1.32	1.51	14.4%	0.298	0.398	0.367	68.5%
(v) Sample Restrictions									
No 3-digit programs	2,403	2,479	1.28	1.50	16.9%	0.298	0.396	0.360	63.4%
Only Ages 40–49	688	885	1.23	1.50	21.9%	0.265	0.311	0.291	56.4%

Notes: Columns (a) display the number of observations in each case in thousands of individuals for both 1980 and 2018. Columns (b) show our measure of assortative matching $\mathcal{S}$ derived in Section 4 for both years along with the percentage change. Columns (c) show the observed Gini coefficients in each case for 1980 and 2018. Columns (d) show the counterfactual Gini coefficient in the fixed marriage market scenario (i), i.e., had the composition of households stayed fixed at its 1980 level in each case and the fraction of the observed change in Gini that is captured by the change in the counterfactual scenario, $\Delta_{Gini,(i)}/\Delta_{Gini,data}$. Each row shows the columns' statistic for one of the alternative definitions of ambition types.

graduates defined by decade (individuals who graduated before 1990, between 1990 and 2000, and after 2000). Here, we account for the possibility that the signaling value of degrees may change over time (similar to the Goldin (2014) argument that occupations have evolved over time). We define three sub-vectors of characteristics by graduation cohort, $\tilde{x}_i^{80} = (w_{0i}^{80}, g_i^{80})$, $\tilde{x}_i^{90} = (w_{0i}^{90}, g_i^{90})$, and $\tilde{x}_i^{00} = (w_{0i}^{00}, g_i^{00})$, and map programs to types by cohort using the k-means algorithm. While Online Appendix Figure B.7 shows that many large programs are remarkably stable in their characteristics over time, we detect some changes. For example, while an ordinary high school diploma is categorized as a type with low starting wage and high growth early in the sample, these growth opportunities decline over time and the degree moves into the low-low category. Other changes are based on shifts in relative pay levels, which can also revert back. For example, preschool teachers are classified as low-low in the first and last part of the sample, but fall into the high starting wage and low growth category in the 1990s. Both our main conclusions regarding the changes in assortative matching and the relationship between household composition and inequality are unchanged when constructing the ambition types by cohort.

In Panel (ii), we analyze the sensitivity of our findings with respect to the assumption that there are exactly four ambition types. To this end, we repeat the analysis but define three and five ambition types instead of four. Once again, our main conclusions remain the same. While more (fewer) categories lead us to detect a slightly stronger (weaker) increase in assortative matching on educational ambition of 24.9% (15.2%), our conclusions on the role of household composition for rising inequality remain.

In Panel (iii), we vary the clustering variables that we use to construct ambition types. In the first two rows, we only use one our benchmark clustering variables, either wage growth g (the sub-vector of characteristics becomes $\tilde{x}_i = (g_i)$) or starting wages w_0 ($\tilde{x}_i = (w_{0i})$), respectively. In the third row, we use both clustering variables, but use only male outcomes to construct ambition types for both men and women. The concern behind this robustness check is that the endogenous labor supply choices of females, e.g., in response to child birth (Kleven et al., 2019) could bias our way of capturing the signaling value of educational programs by affecting the average starting wages and, especially, wage growth of graduates. Therefore, we only use the starting wages and wage growth of male workers, who have more stable labor supply trajectories, to cluster programs. Finally, in the fourth row, we replace wage growth with one of our direct measures of career flexibility and work-life balance based: the part-time penalty (a measure of inflexibility, recall Section A.5). In all four robustness checks, we find that ambition types constructed with alternative clustering variables continue to reveal significant increments in terms of assortative matching (9.2%–15.7%) and that changes in households' education composition explain significant shares of increasing between-household inequality (33.6%–52.6%). What all these alternative categorizations have in common is that they use a sub-vector of characteristics that correlates with both the earnings potential and the work-life balance attached to the unit of observation, as shown in Table A.3. Thus, our conclusion that AM on career ambition has increased over time and that changes in the marriage market contribute significantly to the rise in between-household income inequality is robust to constructing ambition types differently.

In Panel (iv), we assess the robustness of our findings to constructing ambition types at different levels of aggregation. First, the row labeled *Programs* $\times$ *university* uses a level of observation that is more granular than the education programs used for our benchmark categorization. Specifically, we distinguish between similar programs offered at different Danish universities and define $i' = \text{programs} \times \text{university}$ as our unit of observation for the categorization. As our clustering variables, we use the same sub-vector as in our benchmark, $\tilde{x}_{i'} = (w_{0,i'}, g_{i'})$. The assortative matching trend and the explained share of the inequality increment by household composition in this more disaggregated version of our approach are almost identical to the benchmark. This result is consistent with Appendix Figure B.8, which shows that labor market outcomes w_0 and g are very similar across graduates of the same degree program across universities. Second, the row labeled *Sub-fields* $\times$ *levels* uses a level of observation that is more aggregate than the granular education programs used for our benchmark categorization. We aggregate programs by levels and sub-fields of study and define $i' = \text{levels} \times \text{sub-fields}$ as our unit of observation. Specifically, we consider 48 observation units that we obtain by subdividing each of the four educational levels by sub-field of study. Essentially, sub-fields are a more detailed version of the fields of study used above and in the literature that go across educational levels.[24] The results only change slightly. Assortative matching increased by about 14% and household composition by ambition continues to explain more than 40% of the increasing inequality between households.

B.5.2 Additional Sample Restrictions

In Panel (v) of Table A.3 we provide robustness of the main results to additional sample restrictions. First, we consider a reduced sample that omits all individuals with coarse educational program information. Coarse information is defined as observing only 3-digit degree information rather than 4-digit educational degrees. The latter is standard for Danish citizens but we observe a significant share of immigrants with only 3-digit degree information. Hence this robustness test is informative about the role of immigrants in driving the main results. This specification yields quantitatively similar results for inequality to the baseline: The household composition accounts for 36.6% of the increase in inequality, and the PAM trend is slightly muted, with an increase in assortative matching by 16.9%. Intuitively, part of the increase could be driven by marriages among immigrants who are, based on their coarse educational information, more likely assigned to the low ambition cluster. The second specification in Panel (v) focuses only on individuals aged 40-49, following the cohort approach used in the literature

[24] For example, we consider the STEM sub-fields "Construction" and "Mechanics & Metal" and further distinguish programs within this sub-field by the required level of schooling for entry into the programs, i.e., high school (secondary programs) and college/university (tertiary programs).

(see e.g., Chiappori et al. (2020a)). While this analysis is less representative for the levels and changes in assortative matching and inequality overall population, the evidence shows that our main findings on assortative matching and inequality trends are robust and that any changes in the composition of young individuals is not driving our main results.

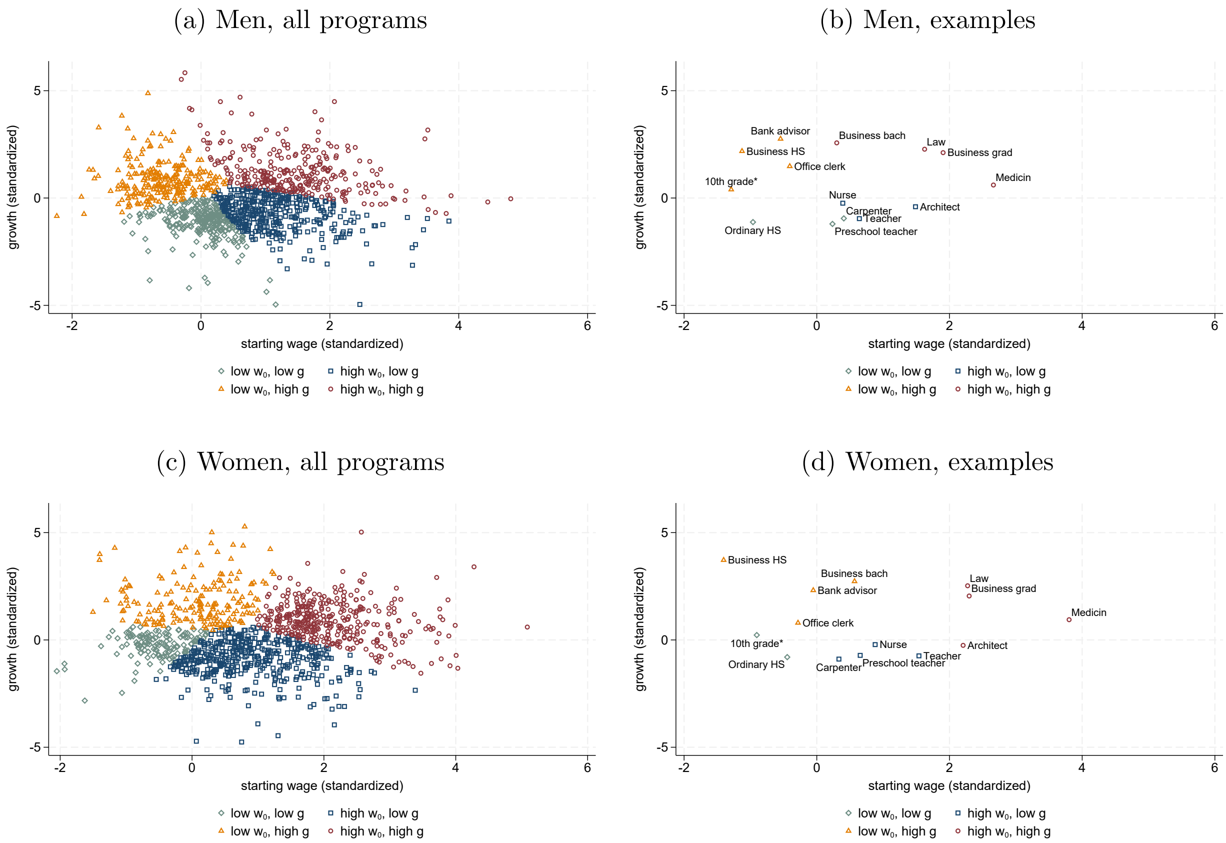
B.5.3 Disposable Income

Finally, Table A.3 provides a comparison of our baseline results for labor income to inequality trends when using disposable income instead. Crucially, this post-tax measure also includes government transfers. We again apply the OECD equivalence scale to analyze inequality in total disposable income across households.

The results of this analysis are reported in the top panel for easy comparison with the baseline. Despite a lower level of inequality, we find a substantial increase in disposable income inequality in the data. 27.7% of this increase can be accounted for by the household composition based on our benchmark ambition types. This evidence shows that redistribution through taxes and transfers does not substantially mitigate the role of marital sorting in explaining inequality trends.

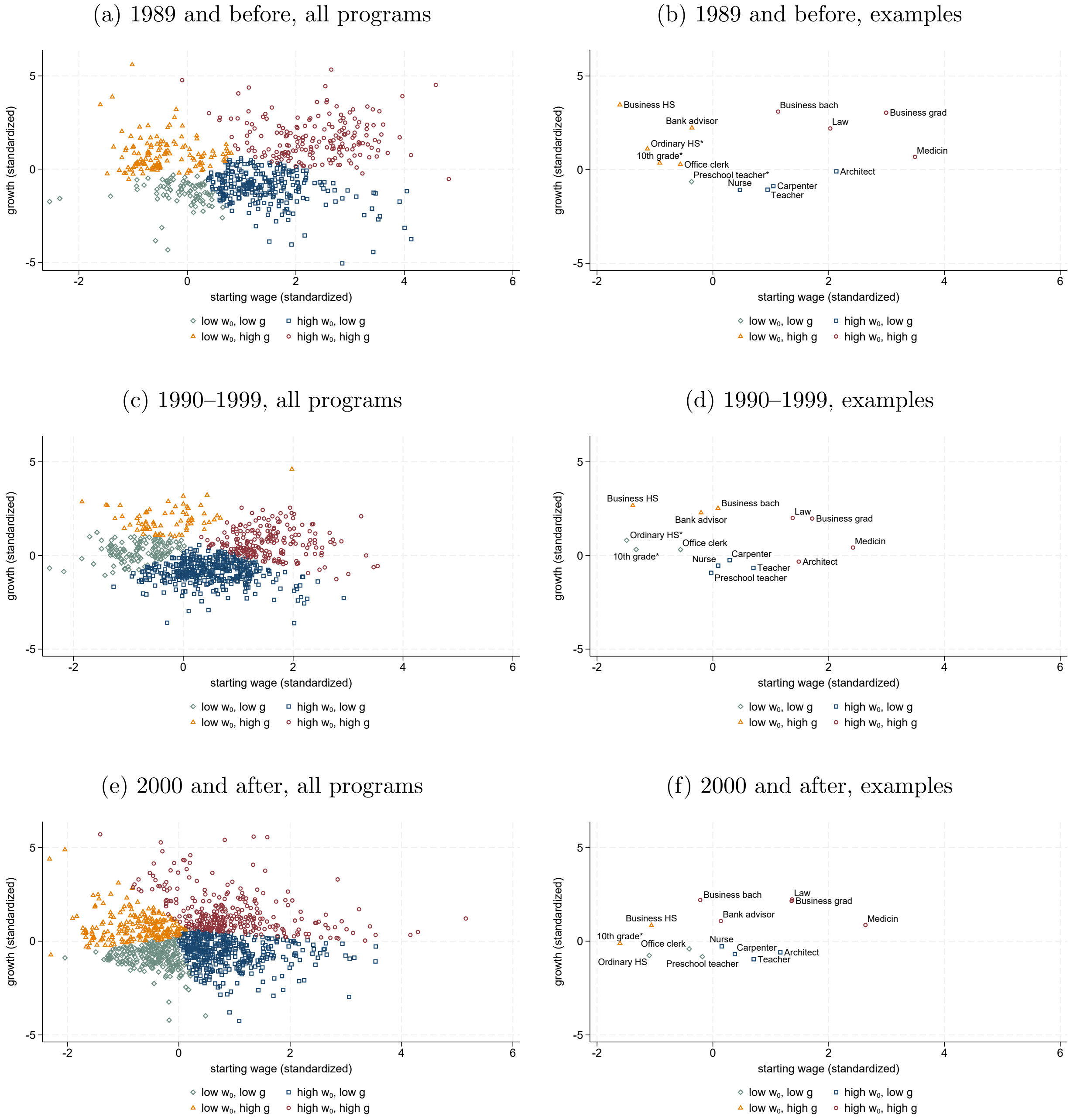
B.5.4 Supporting figures for robustness analysis

Figure B.6: Educational Program Categorizations by Gender



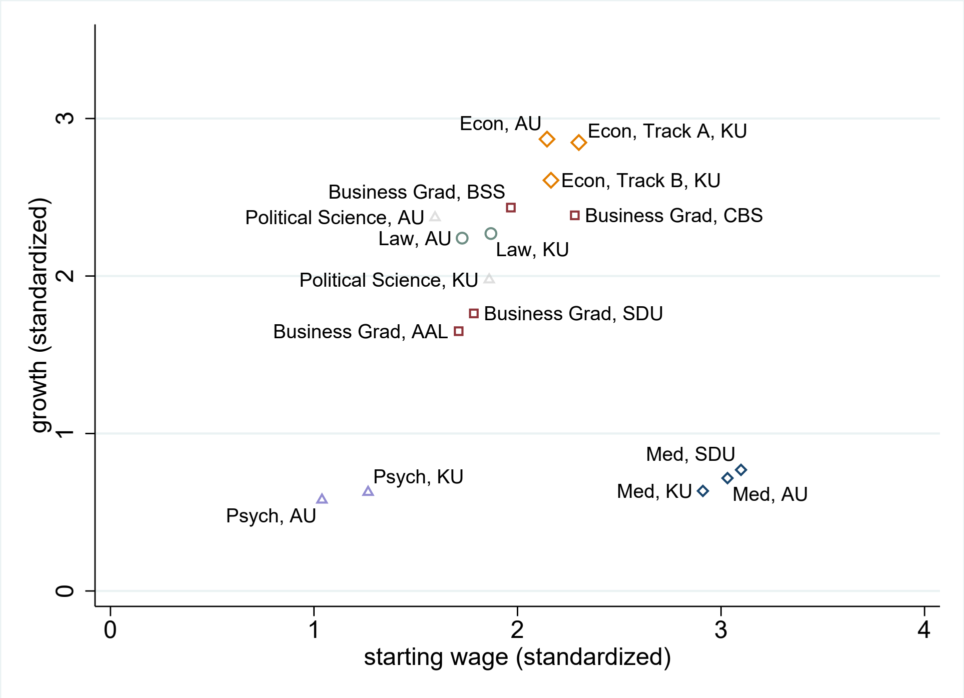
Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The horizontal axis corresponds to the standardized w_0 and the vertical to the standardized g. Points in the panels locate all educational programs with at least ten graduates in 2018—described in Section 2—along these two dimensions. Colors and markers uniquely assign each program to a marriage market type, depending on the panel's definition.

Figure B.7: Educational Program Categorizations by Decade



Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The horizontal axis corresponds to the standardized w_0 and the vertical to the standardized g. Points in the panels locate all educational programs with at least ten graduates in 2018—described in Section 2—along these two dimensions. Colors and markers uniquely assign each program to a marriage market type, depending on the panel's definition.

Figure B.8: Starting Wages and Wage Growth for Main Degree Programs by University



Notes: w_0 stands for *average starting wage* and g for *average wage growth*, defined in Section 3.2. The horizontal axis corresponds to the standardized w_0 and the vertical to the standardized g. Points in the panels locate degree programs by university that have at least 1000 graduates 1980–2018 along these two dimensions. Same symbols and colors indicate the same degree program across different universities.