Educational Ambition, Marital Sorting, and Inequality

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Motivation

- Consensus: positive assortative matching (PAM) in the marriage market (MM)
  1. Evidence for homophily in a number of dimensions.
  2. Literature uses education levels to capture heterogeneity within/across couples.

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  2. Literature uses education levels to capture heterogeneity within/across couples.
- Disagreement: trends in sorting
  1. Is education-based PAM increasing over time?
  2. Is there a link to increasing inequality between households? Literature
- We take a step back and ask:

  What can we learn about marriage-relevant traits using education data?

This Paper

- We use highly detailed education data.
- In Danish register data, we observe detailed education programs.
  - Four-digit program codes (over 1800 unique programs).
  - Examples: carpenter, nurse, doctor, architect, business bachelor/graduate.

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  - labor market (LM) outcomes and career prospects, and
  - signals about the future career-family (work-life) balance.
- We call these novel types Ambition types.

Ambition Types

- Ambition captures expected career prospects.
- We think of the ambition type as a signal in the marriage market.
- It reflects the lifetime career prospects of pre-marital traits.
    1. Expected future career-investments and labor supply.
    2. Expected future time commitments to the family.
- For both reasons, ambition is an important dimension of partner choice.

Key Findings

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- We confirm earlier results about educational-level sorting: no trend.
- But: ambition-based PAM has increased in Denmark.
- It accounts for a substantial share of growing income inequality.
- To overcome the disagreement about the link between MM sorting and inequality, thinking about the definition of education-based types is key.
- Different categorizations lead to different conclusions.

Outline

1. **The Construction of Marriage Market types**
2. The Marriage Market Value of Educational Ambition
3. The Measurement of Sorting
4. Marriage Market Sorting and Inequality

Conceptual Framework

- Women and men are distinguished by their education program:

$$i \in \mathcal{P} = \{Program_1, Program_2, ..., Program_I\}$$

- Programs are characterized by a vector of *selected* characteristics, $\tilde{x}$.
  - e.g.: length, field, average starting wage, average wage growth.

- A mapping that constructs $T < I$ types by grouping programs based on $\tilde{x}$:

$$\mathcal{T}_{\tilde{x}} : \tilde{x} \rightarrow t = \{Type_1, Type_2, ..., Type_T\}$$

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$$\mathcal{T}_{\tilde{x}} : \tilde{x} \rightarrow t = \{Type_1, Type_2, ..., Type_T\}$$

- Example 1: group based on $\tilde{x} = level_i$:

$$t_{Levels} = \{Primary, Secondary, Bachelor, Master\&PhD\}.$$

- Example 2: group based on $\tilde{x} = field_i$:

$$t_{Fields} = \{Field_1, Field_2, ..., Field_T\}$$

Data

- Danish administrative register data
- All married or cohabiting residents aged 19-60 from 1980-2018
- On average 1,800,866 individuals either married or cohabiting per year
- Stable stock of couples Numbers and Ages
  - Downward trend in legal marriage
  - Upward trend in cohabitation
- Household income is joint labor income of spouses
  - Wages and income from self-employment

Education-Based Marriage Market Types

- Idea: education program is valuable information in the MM.
  - Lifetime Income (Altonji, Blom & Meghir, 2012; Altonji, Kahn & Speer, 2014, 2016; Kirkeboen, Leuven & Mogstad, 2016)
  - Career-family balance (Wiswall & Zafar, 2021; Goldin, 2014).
  - Meeting probabilities (Nielsen & Svarer, 2009; Kirkeboen, Leuven & Mogstad, 2022)
- We show that labor market outcomes at the program level reflect expected lifetime income, *how it is generated*, and time allocation choices relevant to the family.

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  - Meeting probabilities (Nielsen & Svarer, 2009; Kirkeboen, Leuven & Mogstad, 2022)
- We show that labor market outcomes at the program level reflect expected lifetime income, *how it is generated*, and time allocation choices relevant to the family.
- We define education-based MM types in 3 ways.
  - the novel ambition types, based on program-level labor market outcomes.
  - based on the level of education Details Levels
  - based on the field of study Details Fields

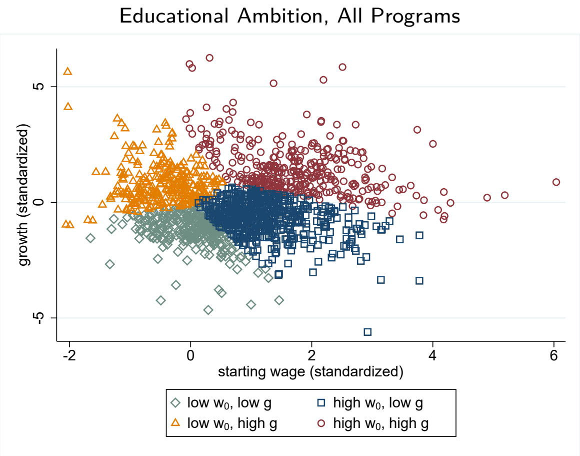
Construction of Ambition Types

- We construct $T = 4$ MM types by grouping the $I = 1800+$ programs,
- based on programs' LM value: *average starting wage* and *average wage growth*:

$$\tilde{x}_i = (w_{0i}, g_i).$$

- Our mapping $t(w_0, g)$ clusters programs using k-means (Steinley, 2006):
  - Use information on life cycle career profiles of all graduates.
  - We focus on the first 10 years after graduation.
  - Deflated log hourly wages
  - $w_0 = \frac{1}{n_p}\sum_{i=1}^{n_p} w_{0i}, g = \frac{1}{n_p}\sum_{i=1}^{n_p} g_i$
    - $w_{0i} = \frac{1}{5}\sum_{y=1}^{5} wage_{yi}, w_{10i} = \frac{1}{3}\sum_{y=9}^{11} wage_{yi}, g_i = (w_{10i} - w_{0i})/w_{0i}$
  - Benchmark - Results robust to alternative specifications

Ambition types successfully capture LM value of education

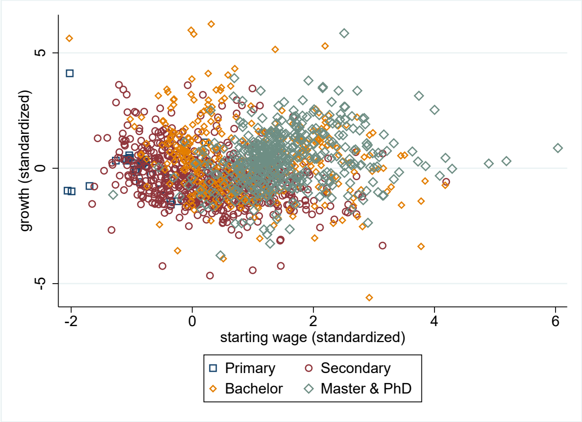


$$t_{Ambition} = \{(low\ w_0, low\ g), (high\ w_0, low\ g), (low\ w_0, high\ g), (high\ w_0, high\ g)\}.$$

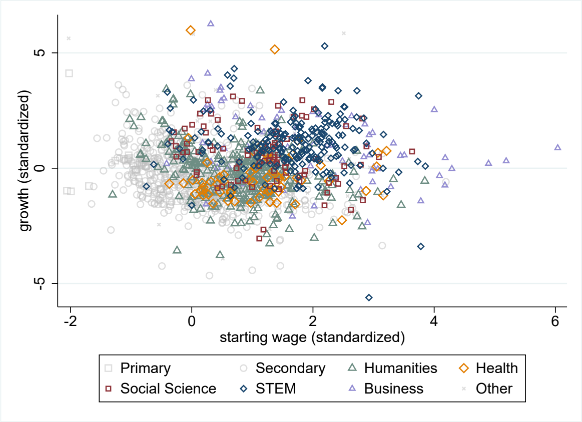
▸ Basic Descriptives ▸ Examples

MM types based on level or field mask heterogeneity in LM value

Educational Levels, All Programs



Educational Fields, All Programs



▸ Levels and Ambition ▸ Fields and Ambition

Outline

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The Marriage Market Value of Educational Ambition

- Our ambition types are unique in that they capture signals about expected future time commitments to career and family.
- High life-time income is not everything, how it is generated matters for the family.
- To show this, we construct seven proxies that capture the trade-off between time investments in career capital and in family responsibilities.
- Example: average ratio of full-time to part-time wages by program.
- Measure of inflexibility or "part-time penalty" (Goldin, 2014)

Ambition type (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	All
Inflexibility $(w_{10}^{FT}/w_{10}^{PT})$	1.052	1.066	1.113	1.119	1.085
	(0.0589)	(0.0755)	(0.0394)	(0.0685)	(0.0658)
Ever manager	0.0286	0.0523	0.0427	0.125	0.0505
	(0.167)	(0.223)	(0.202)	(0.330)	(0.219)
Participation	0.728	0.843	0.729	0.847	0.766
	(0.345)	(0.270)	(0.362)	(0.253)	(0.335)
Full-time if participating	0.770	0.889	0.807	0.850	0.824
	(0.324)	(0.223)	(0.326)	(0.256)	(0.300)
Age first child	29.58	31.37	30.55	31.68	30.70
	(6.163)	(6.321)	(6.878)	(4.832)	(6.342)
Wealth at 50 (mil)	0.198	0.326	0.190	0.679	0.260
	(2.004)	(1.670)	(1.497)	(5.036)	(2.105)
Life-time earnings (mil)	4.772	6.315	5.240	11.39	6.124
	(12.33)	(3.227)	(3.307)	(9.454)	(7.336)

Labor Force Survey

- (*high*, *high*)-program grads more career-focused than (*low*, *low*)-program grads.
- Fix w_0 group, graduates from higher g programs are more career-focused.

FE model:	None	Levels	Fields		None	Levels	Fields	
Controls:	*None*	*None*	*None*	*LT Inc*	*None*	*None*	*None*	*LT Inc*
	(a) Inflexibility				(b) Ever manager			
w_0	-0.009	0.007	0.003	-0.001	0.023	0.025	0.013	0.008
	(0.006)	(0.007)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.006)
g	0.023	0.021	0.016	0.011	0.023	0.027	0.020	0.020
	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)
Mean		1.098		1.081		0.050		0.065
Obs.		985		438		1,837		491
	(c) Participation				(d) Full time work			
w_0	0.054	0.040	0.031	0.016	0.036	0.098	0.087	0.064
	(0.014)	(0.009)	(0.015)	(0.018)	(0.006)	(0.012)	(0.017)	(0.013)
g	0.025	0.037	0.037	0.038	0.008	0.023	0.022	0.013
	(0.009)	(0.007)	(0.009)	(0.012)	(0.008)	(0.008)	(0.010)	(0.008)
Mean		0.766		0.806		0.820		0.853
Obs.		1,837		491		1,837		491
	(e) Age at first child				(f) Wealth at age 50			
w_0	0.305	0.603	0.631	0.106	0.134	0.143	0.133	0.121
	(0.266)	(0.366)	(0.363)	(0.400)	(0.012)	(0.016)	(0.016)	(0.013)
g	0.316	0.368	0.435	-0.022	0.095	0.095	0.087	0.073
	(0.173)	(0.186)	(0.218)	(0.200)	(0.012)	(0.013)	(0.015)	(0.014)
Mean		31.51		31.88		0.241M		0.291M
Obs.		1,824		491		1,309		491

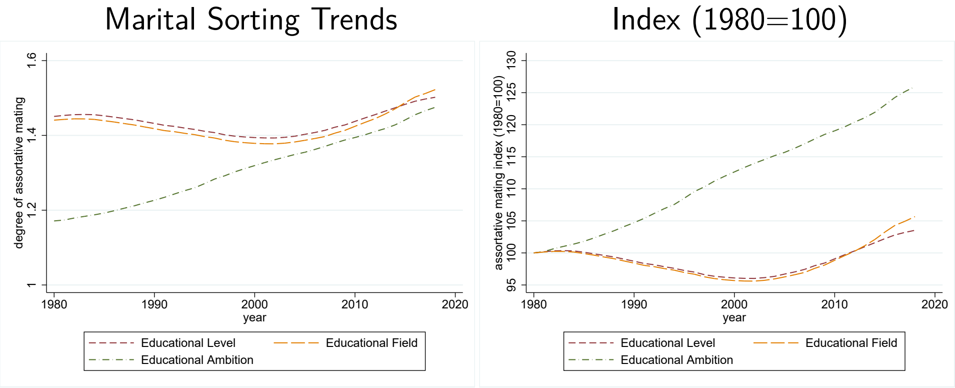
- w_0 or g are significant even within levels/fields and cond. on life-time income.

Outline

The Measurement of Sorting

- We compare trends in sorting for marital types based on educational level, field, and ambition.
- Increased share of assortatively matched couples can occur for two reasons:
  - Marginal distributions vs. Conditional matching probabilities (preferences or frictions)
- We quantify the level of and change in sorting with the weighted sum of likelihood indices (Eika, Mogstad & Zafar, 2019) Details
- Weights make it possible to compare the trend in sorting over time by compensating for changing marginal distributions (Chiappori, Costa Dias & Meghir, 2020; Almar & Schulz, 2024)

Significant increase in sorting on ambition over time



▸ Likelihood Indices ▸ High Type Matches and Marginals ▸ Marginals Ambition & Level ▸ 3 & 5 Ambition Types

- But sorting based on levels or fields does not increase much.
- MM types matter for the conclusion on whether sorting has increased or not.

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1. The Construction of Marriage Market types
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4. **Marriage Market Sorting and Inequality**

Marriage Market Sorting and Inequality

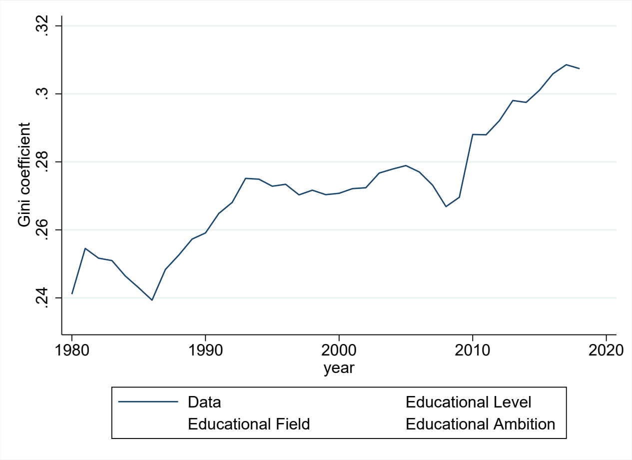
- To study the link between marriage market sorting and inequality, we follow Eika, Mogstad & Zafar (2019) and implement a decomposition exercise inspired by DiNardo, Fortin & Lemieux (1996)

- To this end, we construct a stochastic matching algorithm to re-match married individuals under different counterfactual scenarios:
  i Fixed marriage market sorting
  ii Fixed labor market returns to educational types
  iii Fixed composition in terms of educational types

Decomposition Method Decomposition Table

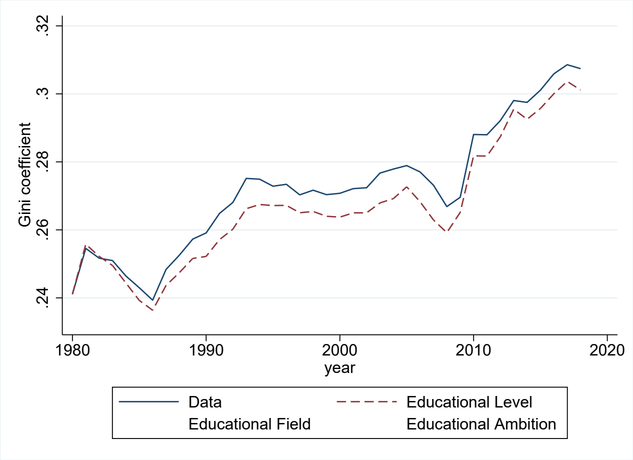
Change in sorting by Ambition explains inequality trends

- Observed increment in inequality between 1980 and 2018 in Denmark:



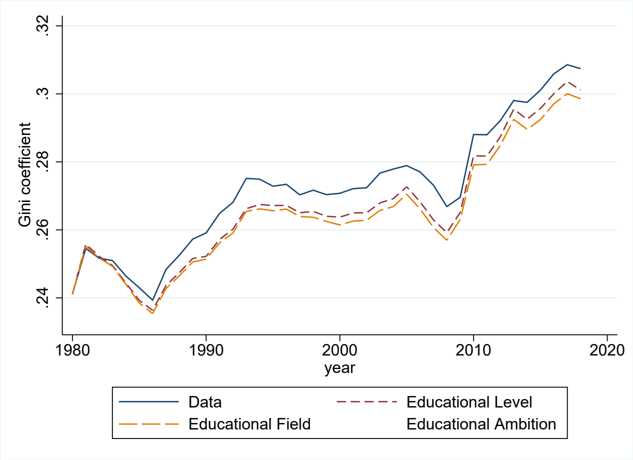
Change in sorting by Ambition explains inequality trends

- Changes in sorting by levels of education contribute little:



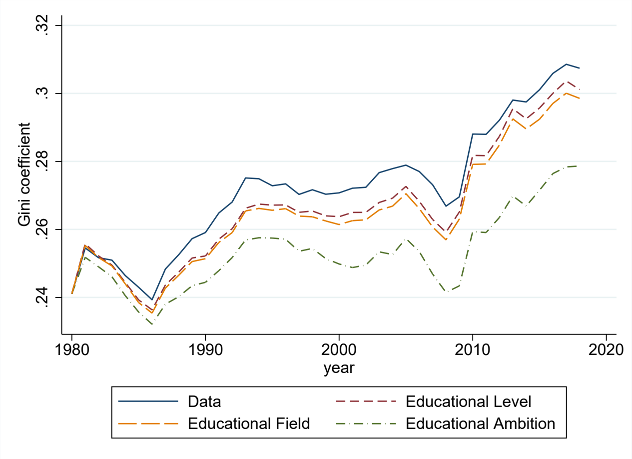
Change in sorting by Ambition explains inequality trends

- Changes in sorting by fields of study contribute little:



Change in sorting by Ambition explains inequality trends

- Increased sorting by ambition explains $> 40\%$ of the increase in inequality:



- MM types matter for whether sorting and inequality trends are related.

Results remain with alternative *Ambition* types

MM types	N (1,000s)		Sorting			Gini, data		Gini, (i)	$\frac{\Delta_{Gini,(i)}}{\Delta_{Gini,data}}$
	1980	2018	1980	2018	Change	1980	2018	2018	
Educational Level	1,758	1,653	1.45	1.50	4%	0.241	0.307	0.301	91%
Educational Field	1,758	1,653	1.44	1.52	6%	0.240	0.307	0.299	87%
Benchmark	1,758	1,653	1.17	1.48	25.9%	0.241	0.307	0.279	57%
Types by gender	1,757	1,651	1.05	1.27	21.0%	0.241	0.307	0.286	68%
Types by cohort	1,742	1,651	1.16	1.50	29.4%	0.240	0.307	0.284	65%
Sub-field level	1,854	1,630	1.19	1.45	21.8%	0.243	0.304	0.279	60%
Three types	1,756	1,653	1.16	1.31	12.7%	0.241	0.307	0.281	60%
Five types	1,756	1,653	1.20	1.58	32.1%	0.241	0.307	0.281	60%

- In all the solid-black alternatives $\tilde{x} = (w_0, g)$.
- Link between trends in sorting and inequality is robust.
- We also show robustness with respect to the Algorithm Performance

Conclusion

- We construct novel *ambition* types that are distinct in their LM and MM values.
  - Cluster education *programs* by average starting wages and wage growth.
- Levels of education and fields of study mask important heterogeneity.
- Between 1980-2018 sorting on ambition increased by more than 25% .
- With fixed sorting in terms of educational ambition at 1980 level, growth of between-household inequality would have been mitigated by about 40%.
- Companion paper “Families’ Career Investments and Firms’ Promotion Decisions”.

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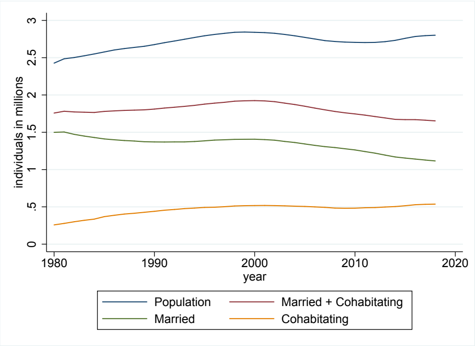
Literature

- Relationship between sorting and inequality.
  - Fernandez and Rogerson, 2001; Greenwood, Guner, Kocharkov and Santos, 2014, 2016; Mare, 2016; Hryshko, Juhn and McCue, 2017; Ciscato and Weber, 2020; Calvo, Lindenlaub and Reynoso, 2022; Kremer, 1997; Breen and Salazar, 2011; Breen and Andersen, 2012; Eika, Mogstad and Zafar, 2019; Gihleb and Lang, 2020.
- Education-based marriage market types and value of degrees.
  - Nielsen and Svarer, 2009; Wiswall and Zafar, 2021; Kirkeboen, Leuven and Mogstad, 2022; Seiver and Sullivan, 2020; Han and Qian, 2022; Artmann, Ketel, Oosterbeek and van der Klaauw, 2021; Altonji, Kahn and Speer, 2014, 2016; Kirkeboen, Leuven and Mogstad, 2016.
- Measurements of sorting.
  - Eika, Mogstad and Zafar, 2019; Chiappori, Costa Dias and Meghir, 2020.

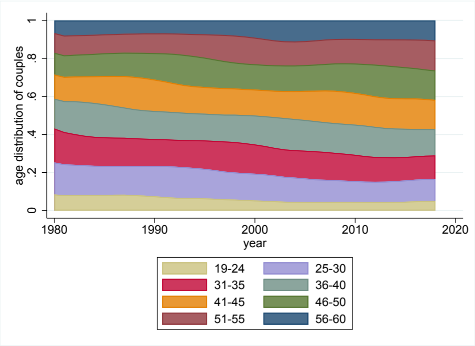
Back

Appendix - Numbers and Ages

Stock of Couples



Age Composition of Couples



Back

Common Categorizations - Levels of Education

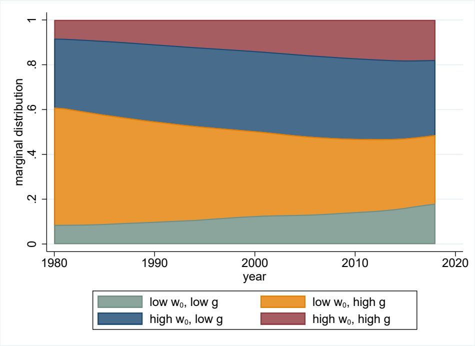
- Four-digit codes identifying graduation from educational programs (HFAUDD)
- We construct a common categorization based on four levels of education, e.g., Eika, Mogstad & Zafar (2019)
  - Primary, secondary, bachelor, and master & PhD
- Large shift in marginal distributions of educational levels 1980-2018
  - Men: Share holding master/PhD multiplied by 3
  - Women: Share holding master/PhD multiplied by 13
  - Marginals Levels
- Back

Common Categorizations - Fields of Education

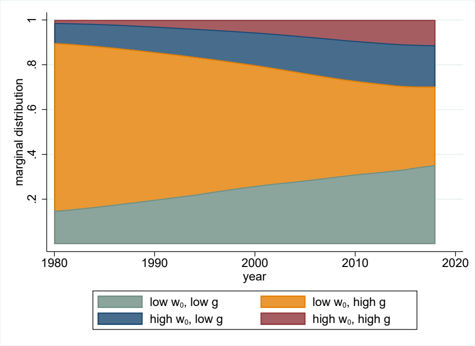
- Recent work suggest the importance of incorporating sorting by fields of study within post secondary education, e.g., Kirkeboen, Leuven & Mogstad (2022)
  - Search frictions are reduced within same field of study
- We keep primary and secondary levels
- We combine bachelor and master & PhD levels and split up into:
  - Education and Humanities
  - Social Science
  - Business
  - STEM
  - Health and Welfare
  - Other
- Back

Appendix - Marginals Ambition Types

Educational Ambition, 4 types, Men

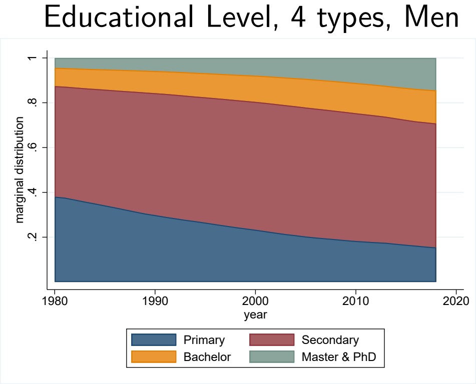


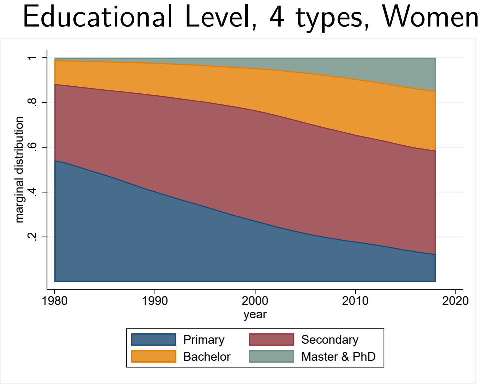
Educational Ambition, 4 types, Women



Back

Appendix - Marginals Education





▸ Back

Appendix - Basic Descriptives

Table: Basic Descriptives

Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Population share	0.202	0.227	0.475	0.0965	
Female share	0.648	0.310	0.560	0.334	0.499
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	401,347.0	664,844.4	269,760.8	1,189,937.8	474,762.7
	(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)

▸ Back

Appendix - Cross Table - Levels and Ambition

Table: Levels and Ambition

Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Primary	8.3%	0.5%	56.2%	0.2%	28.5%
Secondary	66.2%	57.3%	40.1%	10.3%	46.4%
Bachelor	24.1%	29.4%	3.1%	30.3%	15.9%
Master & PhD	0.8%	12.7%	0.5%	59.0%	9.0%

Back

Appendix - Cross Table - Fields and Ambition

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Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Primary	8.3%	0.5%	56.2%	0.2%	28.5%
Secondary	66.2%	57.3%	40.1%	10.3%	46.4%
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%

Back

Appendix - The European Labor Force Survey

Table: Responses to The European Labor Force Survey

Category (w_0, g)	(low, low)	(high, low)	(low, high)	(high, high)	Population
Super full-time work	0.172	0.229	0.219	0.332	0.228
(weekly hours more than 37)	(0.377)	(0.420)	(0.414)	(0.471)	(0.420)
Evening work	0.375	0.428	0.328	0.580	0.402
	(0.484)	(0.495)	(0.470)	(0.493)	(0.490)
Works from home	0.254	0.365	0.298	0.600	0.350
	(0.435)	(0.481)	(0.457)	(0.490)	(0.477)
Works overtime	0.0777	0.108	0.0962	0.158	0.104
	(0.268)	(0.310)	(0.295)	(0.365)	(0.306)

Back

Appendix - The Weighted Sum of Likelihood Indices

Male\Female	$t_{i,f}=1$	$t_{i,f}=2$	$\cdots$	$t_{i,f}=N$	Marginal
$t_{i,m}=1$	$P(1,1)$	$P(1,2)$	$\cdots$	$P(1,N)$	$P(t_{i,m}=1)$
$t_{i,m}=2$	$P(2,1)$	$P(2,2)$	$\cdots$	$P(2,N)$	$P(t_{i,m}=2)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
$t_{i,m}=N$	$P(N,1)$	$P(N,2)$	$\cdots$	$P(N,N)$	$P(t_{i,m}=N)$
Marginal	$P(t_{i,f}=1)$	$P(t_{i,f}=2)$	$\cdots$	$P(t_{i,f}=N)$	1

- Likelihood index

$$s\left(j,j'\right)=\frac{P\left(t_{i,m}=j,t_{i,f}=j'\right)}{P\left(t_{i,m}=j\right)P\left(t_{i,f}=j'\right)}$$

- The weighted sum of likelihood indices

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

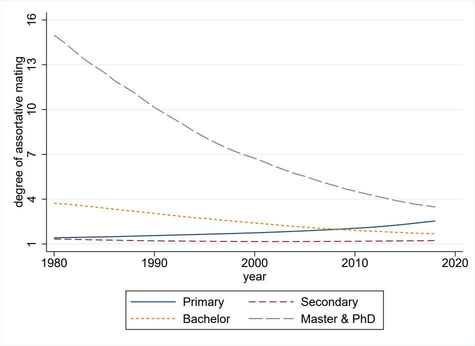
- Product of the marginals weights

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

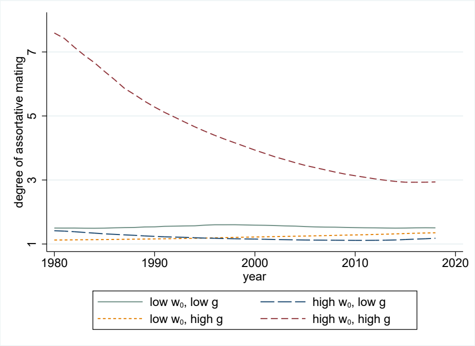
Back

Appendix - Likelihood Indices

Education, 4 types

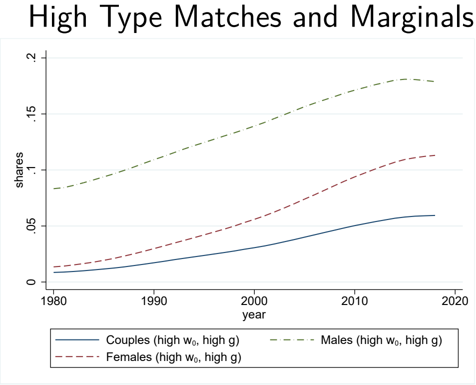


Ambition, 4 types



Back

Appendix - High Type Matches and Marginals



▸ Back

Appendix - Decomposition Method

Scenario (i) - Fixed Sorting

- Resample 2018 males and females according to the 1980 marginal distributions

- Rematching algorithm
  - Treat all (resampled) 2018 individuals as singles
  - Sample potential couples based on (1980) marginal distributions
  - Decide if match or not by a draw from a binomial distribution with p being the matching probabilities of couples implied by the 1980 distribution
  - Non matched individuals returns to pool of singles
  - Reiterate until all have counterfactual match

Back

Appendix - Decomposition Method

Scenario (ii) - Fixed Labor Market Returns to Educational Type

- Construct counterfactual household income distribution

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

- Where we estimate the couple type reweighting factor as follows

$$\widehat{\psi_y} = \frac{P(\tau_x = 2018|x, \tau_p = 2018)}{P(\tau_x = 1980|x, \tau_p = 2018)} \frac{P(\tau_x = 1980)}{P(\tau_x = 2018)}$$

- Use the rematching algorithm to get the 1980 couple distribution using $\tau_p = 2018$

Back

Appendix - Decomposition Method

Scenario (iii) - Fixed Composition in Terms of Educational Types

- For (iiia) and (iiib) start by resampling

- Construct counterfactual household income distribution

$$\widehat{F}(y|\tau_y = 2018, \tau_x = 1980, \tau_p = 2018) = \int F_{Y|X}(y|x, \tau_y = 2018)\psi_x dF(x|\tau_x = 2018)$$

- Where we estimate the couple type reweighting factor as follows

$$\widehat{\psi_x} = \frac{P(\tau_x = 1980s|x, \tau_p = 2018)}{P(\tau_x = 2018|x, \tau_p = 2018)} \frac{P(\tau_x = 2018)}{P(\tau_x = 1980)}$$

- Use the rematching algorithm to get the 1980 couple distribution using $\tau_p = 2018$

Back

	(a) Gini		(b) $^{P90}/_{P50}$		(c) $^{P50}/_{P10}$	
Factual change (Δ_{Data})	0.066	100%	0.165	100%	0.573	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 sorting						
Educational Level	0.060	91%	0.182	110%	0.390	68%
Educational Field	0.057	87%	0.170	103%	0.383	67%
Educational Ambition	0.038	57%	0.089	54%	0.187	33%
(ii) Fixed returns						
Educational Level	0.010	15%	0.127	77%	-0.060	-10%
Educational Field	0.003	5%	0.092	56%	-0.059	-10%
Educational Ambition	0.007	11%	0.080	49%	-0.029	-5%
(iii) Fixed marginals (both)						
Educational Level	0.094	142%	0.197	119%	1.731	302%
Educational Field	0.091	137%	0.184	112%	1.711	298%
Educational Ambition	0.062	93%	0.110	67%	0.750	131%
(iiia) Fixed marginals (male)						
Educational Level	0.060	91%	0.109	66%	0.719	125%
Educational Field	0.058	88%	0.099	60%	0.726	127%
Educational Ambition	0.058	87%	0.121	74%	0.592	103%
(iiib) Fixed marginals (female)						
Educational Level	0.093	141%	0.218	133%	1.125	196%
Educational Field	0.092	138%	0.213	129%	1.102	192%
Educational Ambition	0.067	101%	0.146	89%	0.633	110%

Back

Appendix - Matching Algorithm Performance

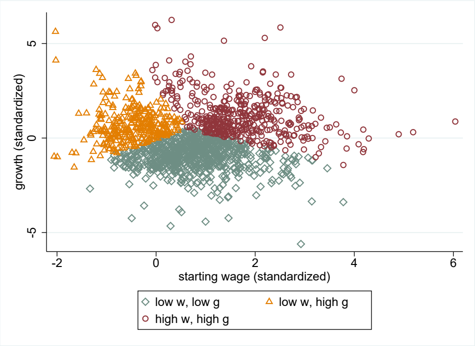
- The matching algorithm is one-dimensional, i.e., it takes only the education-based types into account $\rightarrow$ assume random matching conditional on type.
- If other dimensions correlate with the labor market outcomes that we use to categorize programs, sorting within cells could arise and bias the counterfactual inequality measures.
- Use the algorithm to rematch couples randomly ($p = 0.5$) in 2018 within couple-type-combination cells and check reproduced inequality measures.

	(a) Gini		(b) $P90/P50$		(c) $P50/P10$	
Data (2018)	0.307	100%	1.688	100%	2.518	100%
Within-cell reshuffling						
Educational Level	0.291	95%	1.675	99%	2.178	87%
Educational Ambition	0.295	96%	1.690	100%	2.189	87%

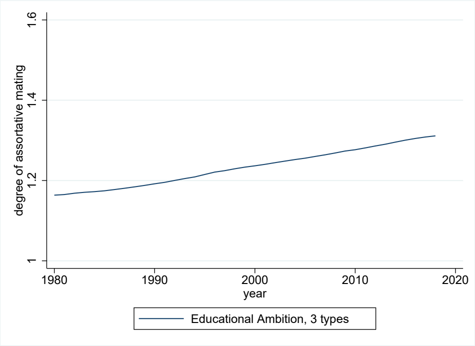
Back

Appendix - Educational Ambition, 3 Types

Categorization

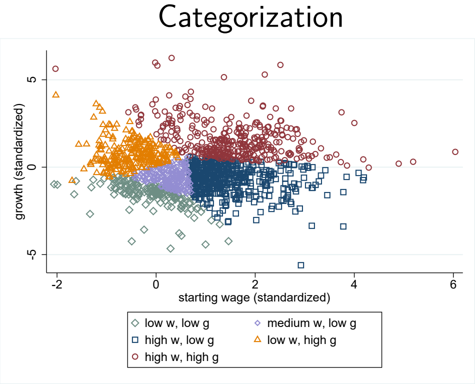


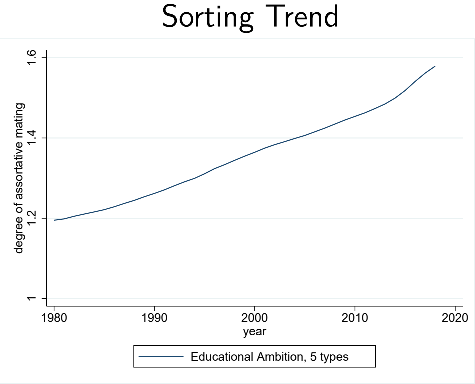
Sorting Trend



Back

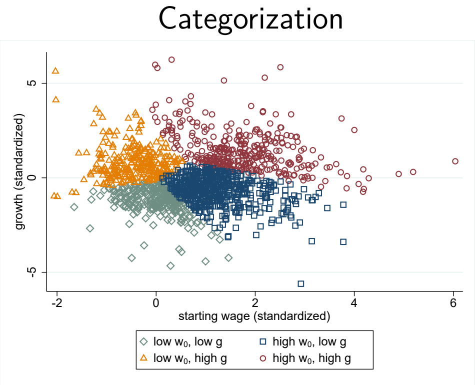
Appendix - Educational Ambition, 5 Types

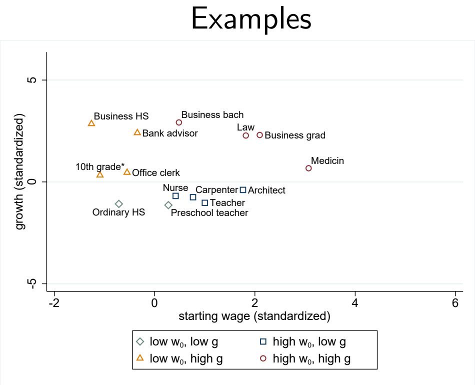




Back

Appendix - Educational Ambition, Examples





- Business graduate “more ambitious” than architect, despite same level.
- Doctor “‘more ambitious” than Nurse, despite same field.

Back