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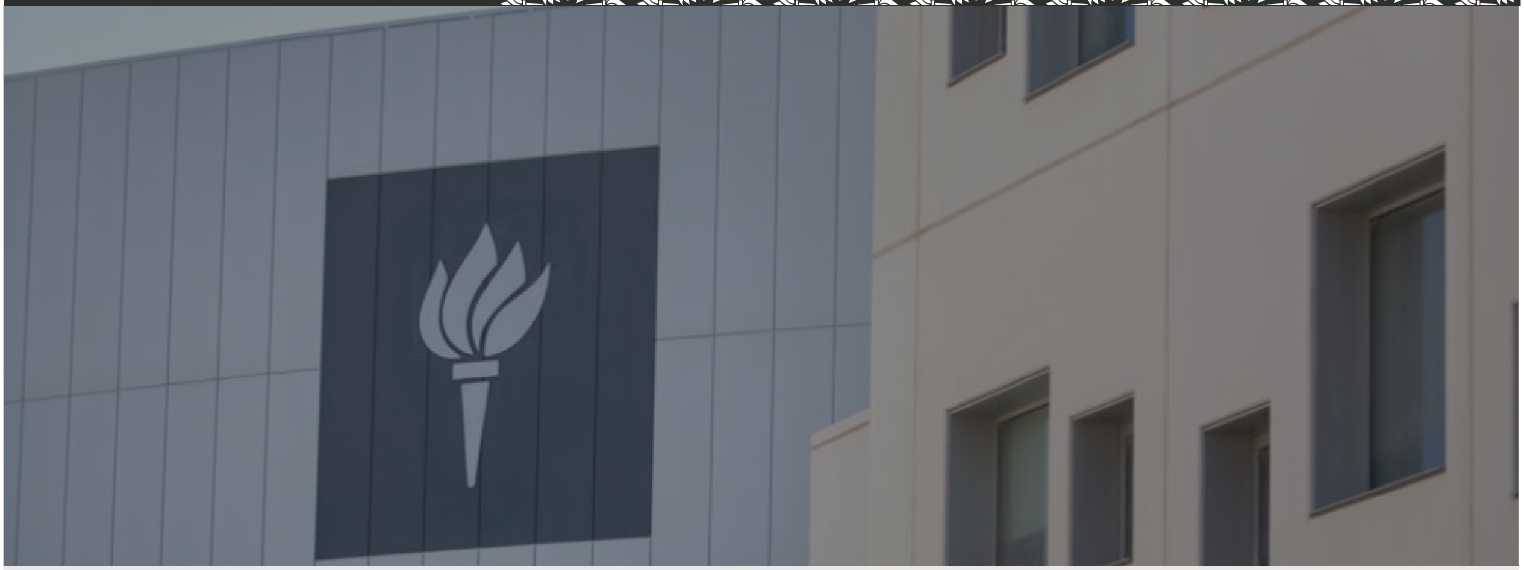

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Specializing in growing sectors: Wage returns and gender differences*

Jennifer Graves[†] **Zoë Kuehn**[‡]

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For eight high-income OECD countries we match individual data with national statistics to test whether those who specialized in fields of study when related sectors were growing later earn higher wages. We estimate 2-3% higher hourly wages for these individuals compared to others of similar characteristics and abilities who made their specialization choices under comparable macroeconomic conditions, and who specialized in the same field but when related sectors were not growing. We also find that men overall are less likely to specialize in growing fields because they avoid traditionally female fields that have grown more over recent decades (e.g. health care or education). While for men with at least a bachelor's degree, specializing in traditionally female fields is associated with lower wages, this is not the case for men with vocational degrees, for whom non-wage factors must drive their reluctance towards female fields. Gendered specialization choices, paired with growth in sectors related to traditionally female fields can generate around 20-30% of the reduction in gender wage gaps in recent decades.

JEL classification: I21, I23, J24, J16, O57

Keywords: higher education, specialization, sectors, wages, gender, PIAAC

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1 Introduction

Higher education decisions constitute one of the largest individual lifetime investments, and economic conditions at the time of such investments matter. Individuals who graduate during recessions have lower lifetime earnings (e.g. Kahn [2010], Oreopoulos, von Wachter and Heisz [2012] or Altonji, Kahn and Speer [2016]). Another important determinant of lifetime earnings are specialization choices in higher education. For instance, the variation in earnings across college majors is almost as large as the average wage gap between college and high school graduates (e.g. Altonji, Blom and Meghir [2012], Arcidiacono [2004]). Surprisingly, little is known about the joint effects of economic conditions and specialization decisions on earnings.[1]

Using individual data matched with national statistics, the current paper tests whether choosing a field of study when related sectors are growing matters for future wages. To this end, we compare individuals of similar characteristics and abilities who made their specialization choices under comparable macroeconomic conditions and who specialized in the same field. In particular, we show that those who specialized in fields of study when corresponding sectors were growing earn 2-3% higher hourly wages in 2011 (on average, roughly a decade after graduation). We then analyze *who* chooses fields of study associated with growing sectors, and we find men to be much less likely to specialize in growing fields, because they avoid traditionally female fields whose related sectors have grown more over recent decades (e.g. health care or education). This begs the question of whether men might be foregoing wage benefits. We find that this is not the case for men with at least a bachelor's degree, for whom specializing in traditionally female fields is associated with lower wages. However, we do not find the same result for men with vocational degrees, for whom non-wage factors (e.g. gender identity as suggested by Aklerlof and Kranton [2000]) must drive their reluctance towards female fields. For five countries in our sample we then show that our estimates for wage returns to specializing in growing fields, together with gender differences in specialization choices, can generate around 20-30% of the reduction in gender wage gaps between 1980 and 2012.

For our analysis, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC) on individuals aged 20-65 who obtained post-secondary degrees be-

[1] The only other two papers we are aware of are Altonji, Kahn and Speer [2016] who show that the effects of recessions at graduation on labor market outcomes differ by field of study, and Blom, Cadena and Keys [2015] who find that exposure to recessions early in life impacts choice of field of study.

tween 1980 and 2010 in the United States, the United Kingdom, Germany, France, Spain, Japan, Sweden, and Finland. PIAAC data includes both educational choices and subsequent labor market outcomes, as well as individual characteristics and detailed measures for ability. PIAAC data also provides variation in the timing (cohorts) and levels of higher education completed (university and vocational degrees). Using information on individuals' fields of study and years of graduation, we match PIAAC data to national statistics on value-added shares of related sectors, and we create an indicator for whether sector shares related to certain fields of study were growing at the time individuals made their specialization decisions. To make sure that this indicator is a meaningful predictor for labor market opportunities in different fields of study, we first show that sector growth at the time of specialization has significant predictive power for sector growth at graduation, which is likely to matter for initial job placements and entry wages. We also show that growth in value added by field is mirrored by growth in employment and that controlling for time-invariant individual characteristics, higher growth in certain sectors is correlated with more individuals choosing related fields of study.

Certain endogeneity issues make estimating the wage effects of choosing fields of study associated to growing sectors challenging. For instance, students who specialize in growing sectors could simply be of higher ability. We address this issue by including detailed measures for individuals' cognitive and non-cognitive ability into our regressions. We also control for macroeconomic conditions at the time students made their specialization choices to account for the possibility that certain high-wage (low-wage) sectors could be more likely to grow during booms (recessions). Additionally, individuals who choose certain fields may be different than others in ways reflected in their wages but not by our controls. For this reason, we also include field and field-by-country fixed effects into some specifications of our wage regression. Identification of the wage effect in these specifications is in the same spirit as that used in studies on wage effects of graduating in a recession. However, in such studies economic conditions are measured in the year of graduation, whereas we use sector-specific economic conditions measured at the time of specialization.[2] Our results hence indicate that even among individuals specializing in the same field within the same country, those who did so when related sectors were growing earn higher wages later on. One issue we

[2]We measure sector growth at the time of specialization because we want to consider a moment in time when individuals can still adapt their specialization choices. Our analysis is hence motivated by literature on college major choice and their finding on the important role of predicted future earnings (e.g. Berger [1988], Arcidiacono et al [2012], Wiswall and Zafar [2015], Choi, Lou and Mukherjee [2016]). However, unlike most of this literature the current paper does not model individuals' specialization choices.

cannot address with our data however is the fact that growing sectors might imply a larger supply of graduates in related fields which could depress wages. Given that such labor supply effects would most likely bias our estimates downward, we interpret our results of 2-3% higher hourly wages for choosing growing fields as lower bounds.[3] We also find that the positive wage effects of specializing in growing sectors are driven by those who later work in occupations related to their field of study.

Our finding of higher wages later in life for those choosing fields of study related to growing sectors, paired with evidence that men are less likely to specialize in growing fields, seems to stand in contrast to existing studies that typically indicate that male students take expected earnings more into consideration than female students when making specialization decisions (e.g. Zafar [2013], Long, Goldhaber and Huntington-Klein [2015], Montemarquette, Cannings and Mahseredijan [2002]). However, our finding is driven entirely by the fact that men avoid traditionally female fields whose related sectors have grown more over recent decades. Whereas most literature finds that such gender differences in specialization choices play an important role for explaining men's higher wages (e.g. Black et al [2008], Gemici and Wiswall [2014], Machin and Puhani [2003]), recent studies suggest a negative relationship with gender gaps. For instance, Ngai and Petrongolo [2017] show that the rise of the service sector (being female dominated) can account for some of the narrowing of gender gaps in hours worked and wages.[4] In a similar spirit, Cortes, Jaimovich and Siu [2018] attribute the simultaneous decrease of college educated men and the increase of comparable women in cognitive/high-wage occupations to a growing valuation of "female" skills (especially social skills). Our findings that suggest an important contribution of gendered specialization choices for the reduction in gender wage gaps contribute to this recent literature by highlighting both labor market benefits to women as female fields grow, but also the potential negative effects for men due to their reluctance to specialize in these fields. Blom, Cadena and Keys [2015] find that women are more responsive than men in adjusting their choice of major during recessions. While their findings point to a greater adaptability of women, ours highlight the lack thereof on the part of men.

Finally, few studies on the effect of economic conditions on education decisions and labor

[3] Our analysis implicitly assumes a perfectly elastic supply of college or vocational training slots which is unlikely to hold across all countries in our sample. However, as long as slots are rationed according to measures included in our regressions, such as individual ability or macroeconomic conditions, this does not pose a threat to our estimation.

[4] Literature documenting the decline in US manufacturing employment and the rise in the service sector caused by import competition from China has recently shown that this affected employment and earnings, but also mortality, differently for men and women (Autor, Dorn and Hanson [2019]).

market outcomes consider countries other than the United States. Aina, Baici and Casalone [2011] and Messer and Wolter [2010], who look at Italian and Swiss university graduates respectively, both find labor market conditions to have a significant impact on individuals' time-to-degree. Beffy, Fougère and Maurel [2012] estimate a low but significant elasticity of college major choice to expected earnings for French university students. For younger students in Spain, Aparicio Fenoll [2016] finds that lower returns to education during a construction boom lead to more boys than girls dropping out of high school. PIAAC data, available for different countries, hence allow us to contribute to this literature with a multi-country analysis of the wage effects of specializing in fields of study associated to growing sectors. In addition and different from most existing literature, our data include not only individuals with college degrees but also those with post-secondary non-tertiary degrees (so-called vocational, professional, or associate degrees).

The remainder of this paper is organized as follows: In Section 2 we describe our data. Section 3 presents descriptive evidence for our variable of growth in related sectors and shows that it is a meaningful predictor for labor market opportunities in different fields of study. Section 4 presents our main estimation of wage effects of specializing in fields of study when related sectors are growing. In Section 5 we analyze who chooses to specialize in growing fields of study. Section 6 discusses the implications of our findings for the gender wage gap, and Section 7 concludes.

2 Data

Our main dataset combines individual data from PIAAC with national statistics on value added shares of sectors. For our analysis we focus on the following eight countries: Finland, France, Germany, Japan, Spain, Sweden, the UK, and the US.[5]

[5]Due to the intensity of data collection and matching of outside data to PIAAC for each country, we limit our sample to eight of the twenty-four countries that participated in PIAAC. Aiming for a variety of educational and labor market settings for which common findings are likely to be generalizable, we choose the sample of countries to represent the following aspects: US as the reference country in the existing literature, Finland a top performer in educational achievement according to PISA, France with a strongly regulated labor market, Germany the largest European economy, Japan the largest Asian economy in our sample, Spain a Mediterranean country, Sweden a Scandinavian country, UK with a similarly flexible labor market as the US.

2.1 PIAAC

The PIAAC survey was carried out by the OECD in 2011 and 2012 and can be described as the adult version of the OECD's better-known Programme for the International Assessment of Students (PISA). While PISA assesses students' cognitive skills, PIAAC does so for a country's population aged 16-65. Apart from cognitive as well as non-cognitive ability scores, PIAAC provides information about individual's schooling, continuous education, work experience, income, and other relevant labor market variables.[6]

For our study, we focus on the following two key variables: First, the survey asks "What was the area of study, emphasis or major for your highest level of qualification?' Answers fall into the following categories: 1) general programmes; 2) teacher training and education science; 3) humanities, languages and arts; 4) social sciences, business and law; 5) science, mathematics and computing; 6) engineering, manufacturing and construction; 7) agriculture and veterinary; 8) health and welfare; 9) services.[7] Second, we have information on individuals' highest educational degrees (ISCED: 0 to 6).[8] Since fields of specialization are not particularly meaningful at lower levels of education, we restrict our sample to individuals age 20 and above with post-secondary education including university as well as vocational degrees (ISCED 4B or above). We also exclude individuals specializing in 1) general programmes or 9) services, because we cannot map these generic fields of study to specific sectors. Finally, we drop individuals who report to have finished their studies in 2011 or 2012 because we cannot be sure that their reported income corresponds to wages earned after graduation.

While PIAAC is a single cross-section, it includes both the age at which each individual finished their degree as well as their current age.[9] We can therefore back out the year in which individuals completed their degree. Data on individuals of different ages allow us to make use of variation over time in growing sectors. In particular, for each observation we

[6] A potential limitation of PIAAC compared to other datasets (e.g. labor force surveys for individual countries) arises from its smaller sample size. However, we want to analyze the relationship between wage outcomes and growing sectors at the time individuals made their specialization decisions for different countries. Hence, the fact that PIAAC data includes information on fields of specialization and is comparable across countries outweighs this limitation.

[7] Such use of aggregate categories for fields of specialization is common in related literature. For example, Berger [1988], Arcidiacono et al [2012], Arcidiacono [2004] and Wiswall and Zafar [2015] each use between four and six categories.

[8] ISCED stands for International Standard Classification of Education designed by the United Nations to be comparable across countries. For details see http://www.uis.unesco.org/Education/Pages/international-standard-classification-of-education.aspx.

[9] For the US and Germany we only have information on year of graduation in 5-year intervals, and we randomly assign individuals to years of graduation within each interval.

merge data from national statistics on value added shares of related sectors in the year each individual was most likely to have made his or her specialization decision. For example in the United States, individuals obtaining a vocational degree typically define their specialization before entering, i.e. 2 years before graduation. For a bachelor's degree a 3-year lag between specialization and graduation is more appropriate as most students define their major during their freshman year. In other countries, such as Spain, specialization decisions at the university level are typically made in the final year of high school, before entering university. Table 1 displays these typical lags for each country. To define these lags we relied on sources such as required years for declaring a major at top universities as well as official guidelines for the duration of studies.[10] We also consider an alternative assignment of PIAAC data to national statistics, assuming that individuals made their specialization choices when they were 18 years old. Given that the vast majority of individuals go directly from high school into post secondary education, it is not surprising that our main findings are robust to this alternative timing assumption.

Table 1: Decision years for specialization relative to graduation in t, by country and degree

	Vocational	Bachelor's
United States	$t-2$	$t-3$
United Kingdom	$t-2$	$t-3$
Finland	$t-4$	$t-4$
France	$t-2$	$t-3$
Germany	$t-3$	$t-4$
Japan	$t-2$	$t-4$
Spain	$t-2$	$t-4$
Sweden	$t-2$	$t-3$

Regarding wages, for Germany, Sweden, and the United States, PIAAC only provides information on wage-deciles. For these countries we assign values to mean wages per decile as proposed by Hanushek et al. [2015]. We also follow the authors' suggestion and trim the bottom and top 1% of the wage distribution for all countries. To convert wages denominated in national currencies into US dollars we use World Bank data. Note that we only have information on hourly wages for dependent workers but not for self-employed individuals.

Unfortunately PIAAC data does not include information regarding individuals' sectors of employment, and hence we cannot calculate the fraction of individuals who end up working in sectors related to their field of study. However, PIAAC provides data on individuals'

[10] For detailed sources see the Companion Appendix available at https://sites.google.com/site/jenniferannegraves/ and https://sites.google.com/site/zoekuehn/research.

current occupations classified according to the International Standard of Classification of Occupations (ISCO). Hence we are able to construct a dummy variable for whether individuals work in occupations related to their field of study. Starting with the most aggregate ISCO 1-digit code, we are able to assign one occupation (Skilled agricultural and fishery workers) to one field of study (Agriculture and Veterinary). For the remaining occupation-field-of-study matches, we rely on ISCO 2, ISCO 3, and ISCO 4 digit codes (see the Companion Appendix for details). Note that our dummy variable captures only individuals who clearly work in jobs related to their field of study because any unclear cases that are not matched to any of the seven fields of study are recorded as zeros (e.g. chefs or police officers). Finally, we calculate years of (potential) job experience as the difference between individuals' current age and their age at graduation.

2.2 National Accounts

For creating our indicator of whether sectors related to a field of study were growing when individuals made their specialization choices, we rely on national statistics. For the United States we have data on value added shares by sector from the Bureau of Economic Analysis (BEA). Table 2 displays the correspondence between fields of study and economic sectors for the United States. From 1977 onward, value added shares by sectors are available in greater detail, and we can also match the field "Science, mathematics and computing" to the following four sectors: (i) Manufacturing of computer and electronic products, (ii) Manufacturing of chemical products, (iii) Information and data processing services and (iv) Computer systems design and related services. In the case of the United States, value added generated by educational services does not include public education, and we thus approximate the fraction of government's value added corresponding to public education by the share of education in public expenditure.[11] Value added by government and expenditure shares in education are also available from the BEA. On average, our assignment of fields of study to economic sectors covers 67% of US value added. For the remaining seven countries, data on value added of sectors come from national statistics offices and the OECD (see Table A1 in the Appendix). Correspondences between sectors and fields of study for these countries are

[11]This procedure assumes that value added (which for the government is calculated as compensation for employees plus operating surplus) is similar across all government sectors, such that the share of expenditure is representative of the share of value added. Government firms might have a very different relationship between employee compensation and operating surplus which is why we exclude their value added in this calculation.

presented in the Companion Appendix.

Table 2: Correspondence between fields of study and economic sectors: US

Field of study	**Sector**
1946-1976	
Teacher training and education science	Educational services, Government*
Humanities, languages and arts	Information
Social sciences, business and law	Finance, insurance, real estate, rental, and leasing,
	Professional and business services
Science, mathematics and computing	–
Engineering, manufacturing and construction	Mining, Construction, Utilities, Manufacturing
Agriculture and veterinary	Agriculture, forestry, fishing, and hunting
Health and welfare	Health care and social assistance
1977-2012	
Teacher training and education science	Educational services, Government*
Humanities, languages and arts	Publishing industries (includes software),
	Manufacturing of: i) Printing and related support activities,
	Motion picture and sound recording industries
	Broadcasting and telecommunications
	Performing arts, spectator sports, museums, and related activities
Social sciences, business and law	Finance, insurance, real estate, rental, and leasing, Legal services
	Miscellaneous professional, scientific, and technical services,
	Management of companies and enterprises, Administrative and support services
Science, mathematics and computing	Manufacturing of: i) Computer and electronic products, ii) Chemical products
	Information and data processing services
	Computer systems design and related services
Engineering, manufacturing and construction	Mining, Construction, Utilities
	Manufacturing less those assigned to other fields
	Pipeline transportation, Waste management and remediation services
Agriculture and veterinary	Agriculture, forestry, fishing, and hunting
Health and welfare	Health care and social assistance

* a fraction of government value added is assigned to "Education."

For constructing these correspondences we asked ourselves which economic sector(s) most individuals choosing their specializations would have in mind as future sectors of employment. For instance, most individuals specializing in "Health and Welfare" are likely to be considering the health care sector, even though some might see themselves working for a pharmaceutical company or an educational institution. As mentioned before, PIAAC data does not include individuals' current sector of employment, and hence we cannot directly check where individuals end up working. But even if it were possible, the final assignment of individuals to sectors is partly endogenous to our question because someone might end up in a sector unrelated to their field of study precisely because they chose a field when related sectors were shrinking. Hence, for the construction of these correspondences we do not want to consider where individuals end up working, but rather where they saw themselves working in the future when they were making their specialization choices.

To control for aggregate economic conditions at the time of specialization we define a recession dummy that takes on value one in years with two consecutive quarters of negative GDP growth. We also use the share of contracts covered by collective bargaining to capture changes in countries' labor market institutions. Finally, we include government expenditure to GDP to reflect changes in public employment opportunities. Table A2 in the Appendix details the sources for these additional macroeconomic variables.

2.3 Matched Data

For each of the seven fields of study, we first calculate the cumulative growth rate of the share in value added of related sectors over 5 years.[12] If this number is positive - i.e. if sectors corresponding to a field of study were gaining weight in the economy over the past five years - then the respective field is defined as growing. Knowing the field of study and decision year for each individual, we construct a dummy variable indicating whether an individual specialized in a growing field. Our main results are robust to using a continuous measure of growth in value added. However, given that our assignment of sectors to fields of study is imperfect, the continuous variable suffers from measurement error and hence our preferred specification uses the dummy variable.

Our final sample consists of individuals with a post-secondary degree in one of the seven fields. Table A3 in the Appendix displays the summary statistics for our sample.[13] The most common field of study is Social Science, Business and Law (29%), and each country is roughly similarly represented in our sample. Around half of all individuals finished their highest degree after 2000, and 33% hold a vocational degree. We measure non-cognitive skills using categories for the aptitude "readiness-to-learn", which is intended to measure both motivation and learning strategies.[14] For cognitive skills we use proficiency levels in numeracy as defined by PIAAC.[15] Both categorical variables are measured at the time of the PIAAC survey, rather than at specialization, but we expect them to be relatively stable over time. One fourth of individuals in our sample work in occupations that are clearly related to their field of study. Around 60% of individuals chose a field of study when related sectors were growing. All macroeconomic controls are measured in the year when individuals made their specialization choices.

Figure A-1 in the Appendix provides a visual summary of our main variable of interest. Among individuals who specialized in Social Science, Business and Law, 80% did so when related sectors were growing, compared to 20% of individuals who specialized in Engineering. Specializing in growing fields is more prevalent among individuals who finished their studies

[12] Our main results are robust to alternative lengths for cumulative growth rates (3, 4, 6, 7 years); see the Companion Appendix.

[13] For descriptive statistics by country see the Companion Appendix.

[14] The questions that go into the construction of this index bear some similarity to the *Openness* category of the Big Five personality traits which are commonly treated as relatively stable and latent. Ample evidence shows that non-cognitive skills of this type can predict educational and labor market outcomes beyond what is measured by typical cognitive skills (Almlund et al. [2011]).

[15] Very few individuals achieve proficiency level 5, and we hence join levels 4 and 5.

during earlier decades. There is also variation in our variable of interest across countries. More than 70% of US individuals in our sample specialized in fields of study when related sectors were growing, compared to fewer than 50% of Finnish individuals.

3 Descriptive Evidence: Growing sectors

Before estimating the wage effects of choosing a growing field, we check that growth in value added of sectors associated to different fields of study is a meaningful predictor for labor market opportunities. First, we show how growth in sectors' value added relates to growth in employment, and how sector growth at the time of specialization is associated to sector growth upon graduation. Finally, we analyze how sector growth at the time of specialization relates to individuals' specialization choices.

3.1 Growth in value added and growth in employment

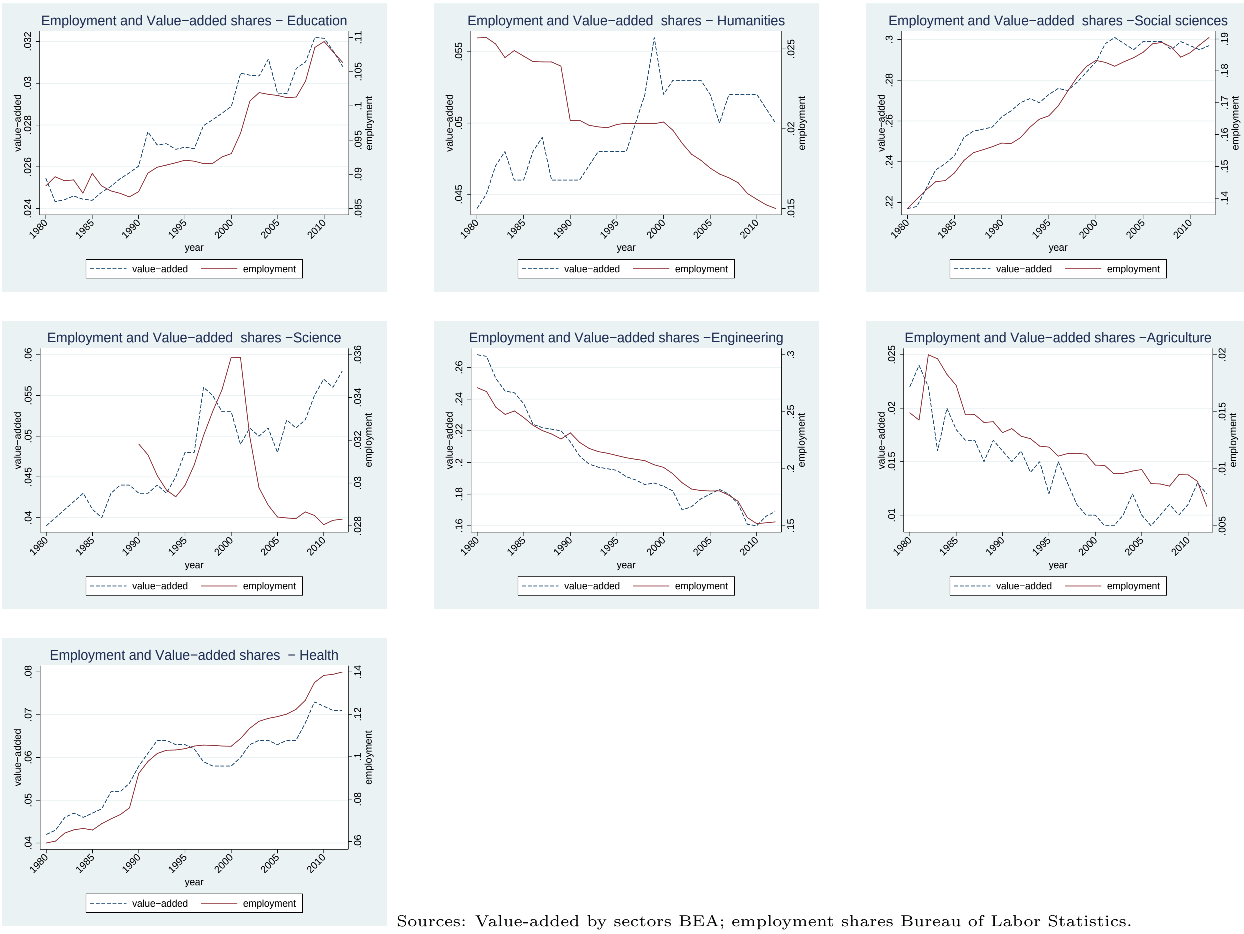
Choosing a field of study when related sectors are growing matters for future labor market outcomes, if such growth reflects growth in employment opportunities. One way to check whether this is the case, is to compare our measure of growth in value added to growth in employment. Figure 1 displays the evolution of employment and value added shares for the seven fields of study for the United States. With the exception of the field "Humanities," both measures are highly correlated.[16]

Note that over the time period considered, value added of sectors related to Education, Health and Welfare, Science, Social Science and Humanities increased while it decreased in sectors related to Engineering and Agriculture. However, these trends are far from smooth and for all fields of study there are years for which individuals specialized in growing or shrinking fields. For instance individuals specializing in Education in 2000 are defined as choosing a growing field while the contrary is true for those who chose the same field of study in 1990.

While a priori it is unclear which measure – value added or employment – provides a bet-

[16] The contradictory movement of value added and employment in "Humanities" is most likely due to the fact that the sector classification of the BEA considers "Publishing Industries including software" while the Bureau of Labor Statistics defines the sector "Publishing Industries except Internet." The Companion Appendix contains similar graphs for employment and value added shares for the UK and Germany as well as details on the construction of these employment shares.

Figure 1: Value-added and employment shares, United States



Sources: Value-added by sectors BEA; employment shares Bureau of Labor Statistics.

ter reflection of labor market opportunities for individuals with post-secondary degrees, we prefer value added shares for two reasons: i) changes in employment shares could be driven by individuals with lower levels of education, in particular considering the strong decline in manufacturing and mining, and ii) as long as labor shares within sectors are relatively constant, changes in value added shares reflect changes in earnings potential.[17]

3.2 Growing sectors at specialization and upon graduation

To capture sector-specific labor market opportunities, our measure of sector growth at the time of specialization should predict sector growth around graduation, when individuals are

[17]However, note that at most value added can only capture changes in average earnings potential, and hence there is no one-to-one correspondence of our measure with wages earned by individuals with post-secondary degrees.

searching for employment. To test whether this is the case, we regress an indicator for whether sectors related to a field of study were still growing when individuals graduated (or one or two years later), on our measure of sector growth when individuals made their specialization decisions

$$growfield_{t+k} = \beta_0 + \beta_1 growfield_{t-4} + \epsilon.$$

Note that for this regression we assume the maximum lag between individuals' decision years and graduation; i.e. 4 years. We carry out the same estimations twice: i) using macro data which includes one observation per year and field of study and ii) using our merged data which gives more weight to years when more individuals in our sample were studying. Results for graduation years, as well as one and two years after graduation are reported in Table 3. Coefficients in column 1 obtained using macro data show that if sectors related to a field of study were growing in any given year, the probability that they were still growing 4 (6) years later is 72.8% (66.5%).[18] Coefficients for the merged data are somewhat smaller but still highly significant.

3.3 Growing sectors and choice of field of study

If choosing a growing field of study matters for future labor market outcomes, one would expect, on the margin, to see more individuals entering a field when related sectors are growing. While our data set is not large enough to test whether this relationship holds in each country, we are able to run the following regression for our pooled sample for each of the seven fields ($f = \text{Engineering, Health Care, Education, ...etc}$)

$$spec_{f,i} = \beta_1 grow_{f,t-2} + \beta_2 grow_{f,t-3} + \beta_3 grow_{f,t-4} + \beta_4 F_i + \beta_5 VD_i + \epsilon_{i,f},$$

where $spec_{f,i}$ indicates whether individual i specialized in field f, $grow_{f,t-2}$, $grow_{f,t-3}$, and $grow_{f,t-4}$ indicate whether sectors related to field f were growing 2, 3 or 4 years before graduation, F_i are time-invariant individual controls including gender, migrant status, and parental education, and VD_i is a dummy variable for vocational degree. Table A4 in the Appendix displays the results from this estimation. With the exception of the relatively

[18] For example, for fields that are not growing in $t-4$, 29.2% will be growing 4 years later, while for fields that were growing in $t-4$, 72.8% will be growing 4 years later. The difference of 43.6 percentage points higher growth is roughly equal to 1.5 times the baseline probability.

Table 3: Predictive power of fields of study related to growing sectors

	Macrodata	PIAAC data
A. Sectors related to field of study grow when graduating in t		
$growfield_{t-4}$	0.436 (0.021)***	0.328 (0.009)***
Constant	0.292 (0.016)***	0.381 (0.007)***
Number of observations	1,786	10,774
R-squared	0.19	0.106
B. Sectors related to field of study grow in $t+1$		
$growfield_{t-4}$	0.35 (0.023)***	0.221 (0.010)***
Constant	0.336 (0.017)***	0.443 (0.007)***
Number of observations	1,730	10,617
R-squared	0.122	0.048
C. Sectors related to field of study grow in $t+2$		
$growfield_{t-4}$	0.313 (0.023)***	0.181 (0.010)***
Constant	0.352 (0.017)***	0.454 (0.008)***
Number of observation	1,674	10,154
R-squared	0.097	0.032

The dependent variable in panels A, B, C are indicators if sectors related to a particular field of study were growing $growfield_{t+k}$ in $k = 0, 1, 2$ respectively. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All regressions are estimated by OLS. Heteroskedasticity robust standard errors.

minor field of Agriculture, we find that, at least for certain lags, growth in related sectors is positively and significantly related to more individuals entering a field of study.

The descriptive evidence presented in this section is supportive of our indicator variable of growth in related sectors as a meaningful predictor for labor market opportunities in different fields of study. Growth in value added by sector aligns well with employment growth, sector growth at the time of specialization predicts sector growth when individuals would be searching for employment and, on the margin, more students specialize in a field if related sectors are growing. We now turn to our main estimation.

4 Wage effects of choosing growing sectors

To test whether choosing a field of study when related sectors are growing matters for future wages, we estimate the following regression,

$$w_i = \alpha_0 + \alpha_1 growfield_{i,t-j} + \alpha_2 Z_i + \alpha_3 VD_i + \alpha_4 x_i + \alpha_5 x_i^2 + \alpha_6 C_{c,t-j} + \alpha_7 D_{D,t-j} + \alpha_8 D_c + \epsilon_{i,c,t,t-j}, \tag{1}$$

where w_i is the natural logarithm of individual i's hourly wage in 2011/2012, $growfield_{i,t-j}$ indicates whether individual i began specializing in a field (in $t-j$) when related sectors had been growing over the past five years. Z_i represents individual characteristics including gender, migrant status, parental education, and measures for cognitive and non-cognitive abilities. $VD_{i,t}$ is a dummy variable for vocational degree, x_i are years of job experience, $C_{c,t-j}$ represents macroeconomic variables measured at the time of specialization, $D_{D,t-j}$ and D_c are decade and country fixed effects respectively, and $\epsilon_{i,c,t,t-j}$ is the error term. We cluster standard errors at the country-field-of-study-year-of-study level. Our main coefficient of interest is α_1, which indicates the subsequent effect on wages of choosing a field of study associated with growing sectors for comparable individuals within the same decade, facing similar economic conditions.

Our estimation faces certain endogeneity issues which we address by including detailed measures for individuals' cognitive and non-cognitive ability as well as controls for macroeconomic conditions at the time students made their specialization decisions. We also include both country and decade fixed-effects to limit comparisons to individuals specializing in generally similar time frames. In addition, one might be concerned that individuals who choose certain fields of study are able to access better paid jobs or that they are different from those choosing other fields, and that these differences are reflected in wages and not captured by our individual controls. To address this concern, we therefore run specifications including field fixed effects, as well as field-by-country fixed effects. In this case the coefficient on $growfield_{i,t-j}$ indicates the subsequent effect on wages for similar individuals who specialized in the same field of study under comparable macroeconomic conditions, but who faced different sector-specific circumstances when making their specialization decisions. The identifying variation behind this estimation is thus in the same spirit as is typically used in estimations of wage effects of graduating in recessions.

4.1 Results

Table 4 presents our estimation results. In column 1 we run the regression without any controls and in column 2 we add individual controls and country fixed effects. Column 3 also includes measures for non-cognitive and cognitive ability. In Column 4 we add macroeconomic controls and decade dummies. Column 5 adds field dummies. Finally, in the most demanding specification, Column 6 adds field-by-country dummies. With the exception of the first column, our estimated coefficient α_1 is positive and significant, and it is robust to the inclusion of different controls. Individuals who chose fields of study when related sectors were growing earn 2-3% higher hourly wages later in life. Note that when including field fixed effects the coefficient drops from 0.029 to 0.021, indicating that wage levels in different fields of study explain some of our results. However, the main effect is due to individuals specializing in fields of study when related sectors were growing. Note that our result is quite robust to either specification, despite the fact that each uses different sources of identification. Without field fixed effects, identification also uses the comparison across individuals choosing different fields and therefore relies much more on controlling for selection on observables. Including field fixed effects however restricts identifying variation to within-field variation over time.

All other coefficients show the expected signs. Returns to experience imply around 3-4% higher wages for the first year, decaying for additional years. Migrants and individuals with a vocational degree earn lower hourly wages, while men, individuals with higher cognitive abilities, and those whose parents have tertiary education earn higher hourly wages. In columns 7 and 8 we test whether the wage effect of specializing in fields related to growing sectors is driven by individuals working in occupations related to their field of study. To this end, we include a dummy variable indicating whether individuals work in jobs related to their field of study, as well as an interaction term between this variable and $growfield_{i,t-j}$. The wage effect of choosing a field related to growing sectors clearly operates through individuals working in occupations related to their specialization.

We test the robustness of our results along various dimensions. Instead of determining individuals' years of specialization by using our country and degree specific lags from one's graduation year, we consider whether sectors related to fields of study were growing when individuals were 18 years old. In this estimation, macroeconomic controls are also measured when individuals were 18 years old. Our results remain robust (see Table A6 in the Appendix). We also estimate a Heckman selection model including the same controls as in

Table 4: Specialization in fields of study when related sectors are growing and hourly wages later in life

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$growfield_{i,t-j}$	-.003	0.023	0.022	0.029	0.021	0.019	0.019	0.0003
	(0.017)	(0.011)**	(0.011)**	(0.011)***	(0.01)**	(0.01)*	(0.01)*	(0.012)
Male		0.173	0.17	0.148	0.136	0.133	0.128	0.129
		(0.01)***	(0.01)***	(0.01)***	(0.011)***	(0.011)***	(0.01)***	(0.01)***
Vocational degree		-.233	-.227	-.200	-.228	-.227	-.224	-.223
		(0.011)***	(0.011)***	(0.01)***	(0.011)***	(0.011)***	(0.011)***	(0.011)***
Job experience		0.037	0.037	0.035	0.036	0.037	0.037	0.037
		(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Experience squared/100		-.070	-.071	-.061	-.063	-.067	-.066	-.067
		(0.009)***	(0.009)***	(0.013)***	(0.012)***	(0.011)***	(0.011)***	(0.011)***
Foreign born		-.091	-.091	-.052	-.053	-.056	-.054	-.054
		(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***
Parental education: secondary		0.025	0.022	0.014	0.014	0.013	0.012	0.012
		(0.012)**	(0.012)*	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Parental education: tertiary		0.059	0.056	0.037	0.04	0.042	0.043	0.042
		(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***
Numeracy: Level 2				0.104	0.108	0.108	0.103	0.103
				(0.025)***	(0.025)***	(0.025)***	(0.025)***	(0.025)***
Numeracy: Level 3				0.176	0.183	0.18	0.175	0.174
				(0.025)***	(0.024)***	(0.024)***	(0.025)***	(0.025)***
Numeracy: Level 4 & 5				0.257	0.254	0.246	0.24	0.24
				(0.026)***	(0.026)***	(0.027)***	(0.027)***	(0.027)***
Works in related occupation							0.108	0.068
							(0.013)***	(0.017)***
$growfield_{t-j}$ ×works related								0.067
								(0.021)***
Country FE		x	x	x	x	x	x	x
Non-cognitive ability			x	x	x	x	x	x
Macroeconomic controls				x	x	x	x	x
Decade dummies				x	x	x	x	x
Field dummies					x	x	x	x
Field-Country dummies						x	x	x
Number of observations	8,018	8,018	8,018	8,018	8,018	8,018	8,018	8,018
R-squared	1.00e-05	0.264	0.267	0.286	0.305	0.319	0.326	0.327

The dependent variable are log hourly wages in 2011/2012. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. Columns 1 to 8 are estimated by OLS. Standard errors are clustered by country, field of study, and year of study. Macroeconomic controls refer to a regression dummy, the % of contracts covered by collective bargaining and government expenditure to GDP, all measured when individuals were making their specialization decisions in $t-j$. Non-cognitive ability measures refer to five categories on the "Readiness to learn" scale defined by PIAAC.

column 4 of Table 4 and with poor or fair health and having children as exclusion restrictions. Table A5 in the Appendix reports results for the full sample as well as separately for women only. Controlling for selection into employment, wage effects of specializing in fields related to growing sectors are in line with those in our main estimation for the entire sample, but they are significantly higher for women. Finally, instead of a dummy variable for growing sectors, we construct a continuous measure using the 5-year percentage point change in the value added share relative to the initial level of value added. Table A7 in the Appendix displays the results. Our results are robust, with the exception of the most demanding specification, reported in column 6, including both field-fixed effects and field-by-country fixed effects, where the estimated coefficient falls short of significance at conventional levels (with a p-value of 0.15).

5 Who chooses growing sectors?

To better understand how choice of growing fields relates to higher wages later in life, we analyze the potential heterogeneity behind our results. In particular, to test *who* chooses growing sectors, we run the following regression

$$growfield_{i,t-j} = \beta_0 + \beta_1 Z_i + \beta_2 VD_{i,t} + \beta_3 C_{c,t-j} + \beta_4 D_{D,t-j} + \beta_5 D_c + \beta_6 D_f + \epsilon_{i,c,t,t-j}, \quad (2)$$

where all variables are as defined before. Our coefficients of interest now are β_1 and β_2 on individual characteristics and the indicator variable for vocational degree, respectively.

5.1 Results

Table 5 presents the results from estimating Equation 5. In general, coefficients for men, foreign born individuals, and those with a vocational degree are negative and significant, indicating that these individuals are less likely to specialize in fields related to growing sectors. We also find some evidence that individuals with higher cognitive abilities are less likely to choose growing fields. When we include an interaction term between male and vocational degree (in column 6), the coefficient for male is smaller but remains negative and significant, while the estimated coefficient for the interaction term is notably larger in absolute value. Hence, in particular, men completing vocational degrees are less likely to choose fields of study related to growing sectors. Notably, when introducing field fixed effects (in column 7), coefficients for variables, such as male, become insignificant, indicating that men being less likely to choose growing fields is a field-specific phenomenon.

In fact, without field fixed effects, the coefficient on male is highly robust. For instance,when running country-specific regressions without field fixed effects, the only robust result is the negative coefficient for men; with the exception of Sweden where the estimate is negative but insignificant (see Table A8 in the Appendix). Our estimated coefficients are also robust to measuring growth of sectors when individuals were 18 years old (see Table A-17 in the Companion Appendix). Furthermore, we check that our result for men is not driven by the last economic and related construction crisis which affected men much more than women. In Table A9 in the Appendix we add a dummy variable for graduating after 2008, as well as an interaction term with male to our main regression. The coefficient for men remains largely unchanged.

Table 5: Individual determinants of specializing in fields of study when related sectors are growing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Male	-.160	-.161	-.162	-.162	-.155	-.104	-.006
	(0.016)***	(0.016)***	(0.016)***	(0.016)***	(0.016)***	(0.016)***	(0.01)
Vocational degree		-.040	-.041	-.040	-.049	0.019	-.018
		(0.018)**	(0.018)**	(0.018)**	(0.018)***	(0.022)	(0.017)
Male×Vocational						-.153	
						(0.027)***	
Foreign born			-.042	-.042	-.054	-.055	-.030
			(0.016)***	(0.016)***	(0.017)***	(0.017)***	(0.015)**
Parental education: secondary			-.006	-.007	-.004	-.005	0.001
			(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Parental education: tertiary			0.0004	-.0005	0.006	0.006	0.006
			(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Readiness to learn 2				0.021	0.025	0.024	0.014
				(0.019)	(0.019)	(0.019)	(0.016)
Readiness to learn 3				-.004	0.001	0.0003	-.003
				(0.019)	(0.019)	(0.019)	(0.017)
Readiness to learn 4				0.012	0.018	0.016	0.015
				(0.02)	(0.02)	(0.02)	(0.017)
Readiness to learn 5				0.025	0.031	0.03	0.019
				(0.02)	(0.02)	(0.02)	(0.017)
Numeracy: Level 2					-.029	-.023	-.020
					(0.022)	(0.022)	(0.02)
Numeracy: Level 3					-.036	-.027	-.018
					(0.021)*	(0.021)	(0.018)
Numeracy: Level 4 & 5					-.078	-.072	-.030
					(0.024)***	(0.024)***	(0.021)
Country FE	x	x	x	x	x	x	x
Macroeconomic controls	x	x	x	x	x	x	x
Decade dummies	x	x	x	x	x	x	x
Field dummies							x
Number of observations	10,774	10,774	10,774	10,774	10,774	10,774	10,774
R-squared	0.069	0.07	0.071	0.071	0.073	0.078	0.248

The dependent variable is $growfield_{i,t-j}$, an indicator for having specialized in a field of study when its related sectors were growing. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. Columns 1 to 5 are estimated by OLS. Heteroskedasticity robust standard errors clustered by country, field of study and year of study. Macroeconomic controls refer to a regression dummy, the % of contracts covered by collective bargaining and government expenditure to GDP, all measured when individuals were making their specialization decisions in $t-j$.

We also check whether a mismatch of fields to sectors could be behind our result of men being less likely to choose growing fields. In particular, sectors related to Engineering, Manufacturing and Construction saw a steady decline over the past decades in every country in our sample (see Figure A-2 in the Appendix). Together with our finding on wage benefits of choosing a field of study when related sectors are growing, this might suggest that individuals who specialize in Engineering, Manufacturing and Construction would be likely to face lower wages, which stands in contrast to a larger trend aiming for more students in Science, Technology, Engineering and Math (STEM) fields.[19] However, an engineering degree, especially at the university level, useful within manufacturing and construction, may also serve as a general signal for ability (also argued in Blom, Cadena and Keys [2015]). To account for the possibility that students majoring in engineering might be considering careers in finance, we alternatively assign to individuals with a university degree in Engineering, Manufacturing and Construction, value added shares of sectors related to Social Science, Business and Law. We then re-estimate Equation 5. Column 1 of Table 6 presents the results. In Column 2,

[19] Recent evidence in Deming [2017] shows that STEM employment in the United States has actually fallen between 2000 and 2012.

the reassignment of fields of study to sectors is limited to university graduates in Engineering, Manufacturing and Construction who also have high numeracy skills. Compared to our benchmark result, the coefficient of interest remains negative and highly significant but is somewhat smaller. The combination of individuals with a university degree in engineering and shrinking manufacturing sectors is thus not the main driver behind our result of men being less likely to choose growing fields.

Table 6: Robustness: Determinants of specializing in fields of study - alternative sector assignment for engineers

	Engineering, Manufacturing and Construction treated as if related sectors were those of Social Science, Business and Law	
	University Graduates	Univ. with high numeracy
Male	-.076 (0.013)***	-.119 (0.015)***
Vocational degree	-.139 (0.022)***	-.082 (0.019)***
Number of observations	10,774	10,774
R-squared	0.078	0.067

The dependent variable is $growfield^{alt}_{i,t-j}$, an indicator for having specialized in a field of study when its related sectors were growing, adjusted such that university graduates in Engineering, Manufacturing and Construction are assigned sectors related to Social Science Business and Law in column 1 and in column2 this reassignment is done for university graduates with Proficiency levels 4 or 5 in numeracy. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. Columns 1 and 2 are estimated by OLS and include the same controls as those in column 6 of Table 5. Heteroskedasticity robust standard errors clustered by country, field of study and year of study.

The contrast between specifications with and without field fixed effects in Table 5 suggests that while men are much less likely to specialize in growing fields, this seems to be driven entirely by the particular fields that they choose. Next, we therefore explore the role of male- and female- dominated fields as an explanation for why men are less likely to specialize in fields associated with growing sectors.

5.2 Mechanism: Genderedness of growing fields

Fields of study are typically very segregated by gender. For the countries in our sample Figure A-3 in the Appendix shows that men are overrepresented in Engineering, Manufacturing and Construction, Agriculture and Veterinary, and Science, Math and Computing, while they are underrepresented in Education, Health and Welfare, and Humanities. Social Science, Business and Law (SSBL), in comparison, is relatively gender-neutral. To analyze how much of our finding that men are less likely to specialize in growing fields can be explained by the genderedness of growing fields, we construct a variable with four categories (k): 1: chose non-growing field, 2: chose female growing field, 3: chose male growing field and 4: chose

SSBL growing. To estimate the potentially differential impact of being male on choosing a growing field (relative to a non-growing field) by whether that field is male-dominated, female-dominated or gender neutral, we run the following multinominal logit regression

$$f(k,i) = \alpha_k + \beta_{1,k} Z_i + \beta_{2,k} VD_{i,t} + \beta_{3,k} C_{c,t-j} + \beta_{4,k} D_D + \beta_{5,k} D_c, \tag{3}$$

where $f(k,i)$ indicates the probability that observation i has outcome k, where $k = 1, 2, 3, 4$. Our baseline category is $k = 1$ (chose non-growing field).

Table 7 displays the coefficients for the variable male from this estimation. Naturally, men are more likely to specialize in male fields and less likely to specialize in female fields. What is interesting here is how the magnitude of these tendencies varies with whether those fields are growing. In all countries, men are less likely to specialize in growing female fields compared to fields that are not growing. While for some countries we also estimate positive and significant coefficients for men specializing in growing male fields, the absolute values of the negative coefficients on growing female fields are always much larger. In other words, men are less likely to choose growing fields, but this is specifically driven by men being less likely to choose growing female fields. In Table A10 in the Appendix we repeat the same estimation separately for men obtaining a vocational degree and for those obtaining at least a bachelor's degree. The aversion towards growing female fields for men with a vocational degree is more than twice as large as for men with a bachelor's degree (the relative risk ratio of specializing in a growing female field is 0.13 for men obtaining a vocational degree compared to 0.35 for those with a bachelor's degree).

Table 7: Men's decision to specialize in growing female, growing male, or growing neutral (Social Science Business & Law) field of study compared to choosing non-growing fields

	All	Fin	Fra	Ger	Jap	Spa	Swe	UK	US
Estimated coefficients for "Male" choosing the following categories:									
Growing female field	-1.372***	-1.576***	-1.567***	-1.633***	-1.783***	-1.102***	-1.245***	-1.015***	-1.420****
	(0.0754)	(0.242)	(0.196)	(0.200)	(0.223)	(0.202)	(0.215)	(0.203)	(0.225)
Growing male field	0.343***	0.513	-0.306	0.563*	0.701	0.578*	0.951***	0.219	0.00607
	(0.102)	(0.399)	(0.208)	(0.325)	(0.557)	(0.336)	(0.192)	(0.398)	(0.251)
Growing SSBL	-0.502***	-1.156***	-0.856**	-0.950***	0.219	-0.344**	-0.253	-0.660***	-0.473**
	(0.0740)	(0.248)	(0.183)	(0.205)	(0.210)	(0.172)	(0.288)	(0.190)	(0.192)

Coefficients from multinominal logit regression marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All columns are estimated by multinominal logit regression of the following categorical variable: 1: chose non-growing field, 2: chose female growing field, 3: chose male growing field and 4: chose SSBL growing. Baseline category is 1. They all include the same controls as those in column 5 of Table 5. Robust standard errors clustered by country, field of study and year of study.

As mentioned before, during the period of our study, the weight of sectors associated with male fields, in particular Engineering, Manufacturing and Construction, decreased in all countries, while value added in female fields such as Health and Welfare and Education increased (see Figures A-4 and A-5 in the Appendix). The one exception is Sweden, where value added in Education suffered a strong decline between 1980 and 2000. Hence, if Swedish women continued to specialize in Education more than men, in our analysis they would be recorded as choosing a field of study that was not growing. This could explain why we estimate a negative but insignificant coefficient for men specializing in growing fields for Sweden in Table A8.

5.3 Mechanism: Gender-specific benefits of choosing growing fields

As a possible explanation for why men are not choosing growing fields, we test whether wage benefits of choosing a field of study when related sectors are growing are gender specific, and whether this depends on the genderedness of the field. Table 8 presents results for our main wage estimation (Equation 1) including controls for gendered fields of study (female, male, SSBL) which we interact with an indicator for growth in related sectors (our omitted category are male fields that are not growing). In columns 2 and 3 we repeat the estimation for men and women separately. In general, men earn higher wages but they experience significant wage penalties when specializing in traditionally female fields, even when those fields are growing (columns 1 and 2). Gains from specializing in fields of study when related sectors are growing are gender-specific. They are only present for women who specialize in either growing female or growing male fields of study.

To test whether both, men obtaining vocational degrees as well as those obtaining a bachelor's degree, suffer wage penalties when specializing in female fields, we run a variant of our previous regression. However, to avoid further cutting the sample, we fully interact gender, gendered fields, and whether related sectors were growing to generate mutually exclusive categories. Our omitted category is "men in shrinking male fields". Table 9 shows the results from this estimation. The coefficient on "men in growing female fields" (compared to "men in shrinking male fields") is insignificant for those with vocational degrees and negative for those with at least a bachelor's degrees. For the latter, specializing in traditionally female fields is associated with lower wages, even if such fields are growing. However, this is not the case for men obtaining a vocational degree for whom specializing in growing female fields or shrinking male fields is associated with equivalent wage outcomes. Hence, men's reluctance to

Table 8: Wage gains from choosing growing female fields of study - by gender

	All	Men	Women
$growfield_{i,t-j}$	0.022 (0.017)	0.01 (0.02)	0.083 (0.03)***
Social Science, Business and Law	0.016 (0.019)	0.002 (0.027)	0.081 (0.026)***
Female field of study	-.071 (0.02)***	-.121 (0.029)***	0.017 (0.027)
SSBL growing	-.013 (0.025)	-.012 (0.035)	-.077 (0.037)**
Female field growing	0.035 (0.025)	0.052 (0.04)	-.040 (0.037)
Male	0.132 (0.01)***		
Vocational degree	-.203 (0.011)***	-.221 (0.016)***	-.173 (0.014)***
Job experience	0.036 (0.003)***	0.042 (0.005)***	0.031 (0.004)***
Experience squared/100	-.061 (0.013)***	-.072 (0.018)***	-.057 (0.015)***
Country FE	x	x	x
Non-cognitive ability	x	x	x
Cognitive ability	x	x	x
Macroeconomic controls	x	x	x
Decade dummies	x	x	x
Number of observations	8,018	3,603	4,415
R-squared	0.289	0.302	0.25

The dependent variable are log hourly wages in 2012. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All columns are estimated by OLS and include in addition the same controls as those in column 4 of Table 4. Standard errors are clustered by country, field of study, and year of study. Macroeconomic controls refer to a regression dummy, the % of contracts covered by collective bargaining and government expenditure to GDP, all measured when individuals were making their specialization decisions in $t-j$. Non-cognitive ability measures refer to five categories on the "Readiness to learn" scale defined by PIAAC.

obtain a vocational degree in growing female fields must be linked to non-monetary aspects, such as preferences, social stigma or discrimination.

6 Implications for the gender wage gap

Our results that i) specializing in growing fields is associated with higher wages later in life and that ii) men are less likely to specialize in growing fields, suggest potential implications of gendered specialization decisions for the gender wage gap. While gender gaps have narrowed over recent decades, closing these gaps remains an important policy focus (see Goldin [2014] or OECD [2013]). In Figure A-6 we plot the evolution of the ratio of value-added in Engineering, Manufacturing and Construction to value added in Health and Welfare, next to the gender wage gap. The growth of sectors associated with female fields relative to sectors associated with male fields has gone hand in hand with a narrowing of the gender wage gap. Linking this to our estimates, in Figure A-7 we graph the change in the gender wage gap for each country against the absolute value of the negative coefficient for men's reluctance to

Table 9: Gendered wage gains from choosing growing female fields of study - by degree type

	All	Voc	Uni
Men in growing female fields	-.066	-.038	-.085
	(0.021)***	(0.039)	(0.025)***
Men in growing male fields	0.005	0.025	-.012
	(0.02)	(0.032)	(0.025)
Men in shrinking female fields	-.127	-.163	-.136
	(0.027)***	(0.062)***	(0.031)***
Women in growing female fields	-.157	-.122	-.184
	(0.015)***	(0.023)***	(0.019)***
Women in growing male fields	-.135	-.094	-.162
	(0.024)***	(0.043)**	(0.03)***
Women in shrinking female fields	-.210	-.170	-.233
	(0.018)***	(0.031)***	(0.023)***
Women in shrining male field	-.216	-.240	-.214
	(0.022)***	(0.04)***	(0.027)***
Men in SSBL	-.001	0.003	-.019
	(0.016)	(0.029)	(0.02)
Women in SSBL	-.126	-.121	-.136
	(0.015)***	(0.024)***	(0.02)***
Vocational degree	-.207		
	(0.01)***		
Job experience	0.035	0.026	0.038
	(0.003)***	(0.005)***	(0.003)***
Experience squared/100	-.061	-.028	-.073
	(0.01)***	(0.016)*	(0.013)***
Country FE	x	x	x
Non-cognitive ability	x	x	x
Cognitive ability	x	x	x
Macroeconomic controls	x	x	x
Decade dummies	x	x	x
Number of observations	8,018	2,555	5,463
R-squared	0.291	0.288	0.264

The dependent variable are log hourly wages. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All columns are estimated by OLS and include in addition the same controls as those in column 4 of Table 4.

go into growing fields (Table A8; note that for Germany, France, and Spain, data on gender wage gaps is only available from 1992, 1995 and 2004 onwards respectively). We observe a positive cross-country relationship, indicating that a greater aversion of men to specialize in fields of study associated with growing sectors is related to a larger reduction in gender wage gaps.

To further examine this relationship, we calculate the reduction in the gender wage gap that can be generated by gendered specialization decisions and our estimated returns. For countries for which data on the gender wage gap is available from 1980 onward (Finland, Japan, Sweden, the UK and the US) we set the difference in wages between men and women to the initial gender wage gap. Then we use our estimates from columns 2 and 3 of Table 8 to assign wage gains and losses to men and women based on their fields of specialization. We then predict the evolution of male and female wages (see Table A11 in the Appendix for the share of men and women in different fields of specialization). Comparing our estimates to the actual change in the gender wage gap, we find that they can explain 58% of the observed change in the gender wage gap in Finland, 28% for the United States, 25% for the United Kingdom, 23% for Japan, and 0% for Sweden (where the actual wage gap increased by 2.4 percentage points between 1980 and 2012 while we predict a decline by 7 percentage points).[20] While these are rough calculations, together with Figures A-7 and A-6 they are highly suggestive of how gendered specialization decisions paired with growth in female sectors could have contributed to a narrowing of the gender wage gap.

7 Conclusion

Choosing a field of study when related sectors are growing results in higher hourly wages later in life. We find this relationship to be quite robust as well as to hold for various countries with distinct educational and labor market contexts. We also provide evidence that the wage effects of specializing in fields associated with growing sectors are driven by those who later work in occupations related to their specializations. Having found positive wage effects, we then explore *who* chooses fields of study when related sectors are growing. Maybe surprisingly given previous findings in literature, men are less likely to choose growing fields compared to women. However, this is entirely due to men's reluctance to specialize in female fields such as health care and education which have grown more over recent decades.

The decline of traditionally male sectors, which has forced displaced workers to change occupations at high costs, has been widely documented (see e.g. Neal [1995]). Different from the consequences that arise to men in their mid-career when sectors decline, our analysis highlights the wage effects of young men's specialization decisions and how these relate to contemporaneous sector-specific economic conditions. In particular, we observe that men

[20] Normalizing wages for men in 1980 to 1, changes in wages for men are calculated as the sum of the proportions of men going into each field type times the wage gains or losses for men entering each field type, where a field type is defined as one of the following six categories: growing female field (Fgrow), not-growing female field (Fngrow), growing male field (Mgrow), not-growing male field (Mngrow), growing SSBL (SSBLgrow), not-growing SSBL (SSBLngrow). Denoting proportions by p and estimates for wage gains or losses by e, wages for men in 2012 can be written as: $w^m_{2012} = p^m_{Fgrow}(1 + e^m_{Fgrow}) + p^m_{Fngrow}(1 + e^m_{Fngrow}) + p^m_{Mgrow}(1 + e^m_{Mgrow}) + p^m_{Mngrow}(1 + e^m_{Mngrow}) + p^m_{SSBLgrow}(1 + e^m_{SSBLgrow}) + p^m_{SSBLngrow}(1 + e^m_{SSBLngrow})$. Wages for women in 1980 are set to the initial gender wage gap and changes in wages are calculated in the same way but using the proportions and estimates for females. As an example take Finland; 18.6% of men in our sample chose female fields of study and thus suffered a wage loss of 12.1%. Wages for men in 2012 are hence predicted to be $w^m_{2012} = 0.186(1 - 0.121) + (1 - 0.186)$. For women we estimate $w^f_{2012} = w^f_{1980}[(0.526 - 0.189) * 1.083 + (0.304 - 0.189) * 1.081 + 0.189 * 1.004 + (1 - 0.526 - 0.304 + 0.189)]$. The implied relative female wage in 2012 is the ratio of these two.

obtaining a vocational degree avoid specializing in female fields, even as related sectors are growing. Since we find no difference in wage outcomes for men between obtaining a vocational degree in growing female or male fields, their reluctance to specialize in growing female fields must therefore be linked to non-monetary aspects such as preferences, social stigma or discrimination.[21] Our results suggest that gendered tendencies in specialization decisions, paired with growth of sectors related to traditionally female fields could have contributed significantly to narrowing gender wage gaps in recent decades.

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[21] Anecdotal evidence suggests that part of this reluctance might arise from wives' reluctance to see their husbands working in female sectors (see Chira [2017]).

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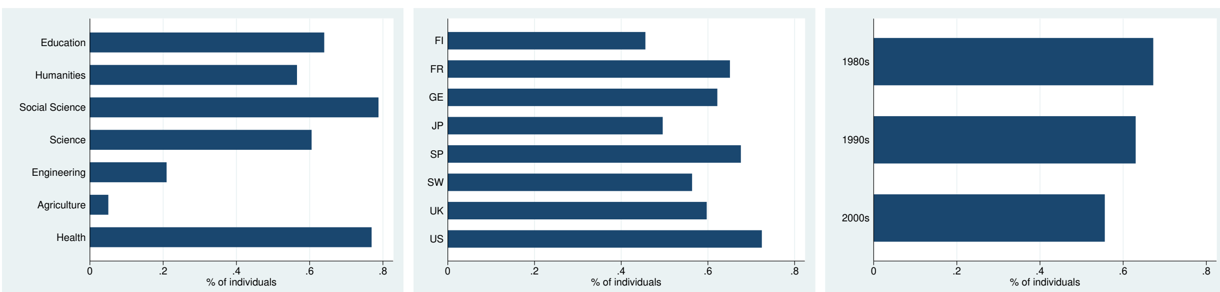
A Appendix

A.1 Figures

Figure A-1: Fraction of individuals who specialize in a field of study when related sectors are growing by field, country, and decade



PIAAC and national accounts data for each country. Authors' own calculations.

Figure A-2: Value-added share of sectors associated to field of study "Engineering Manufacturing and Construction"

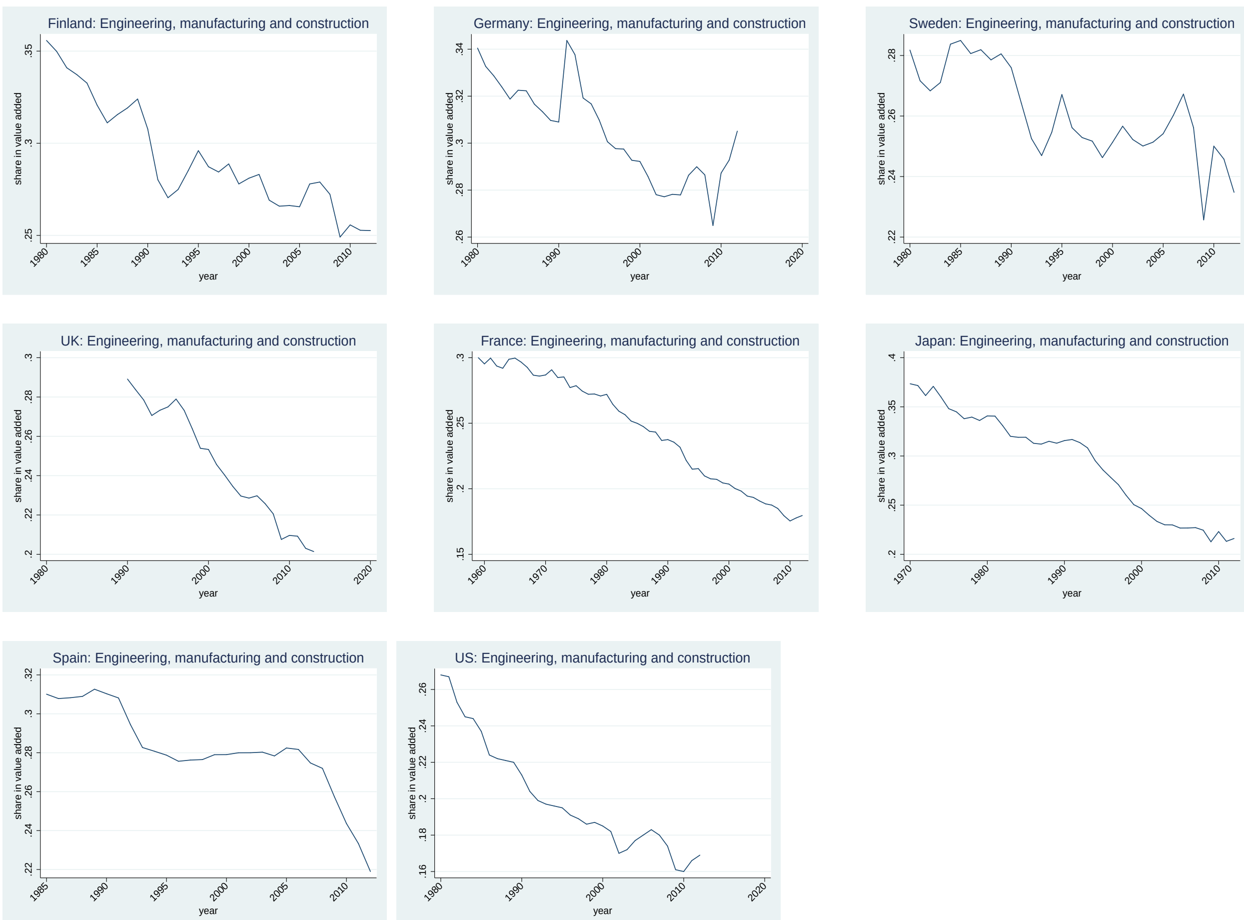
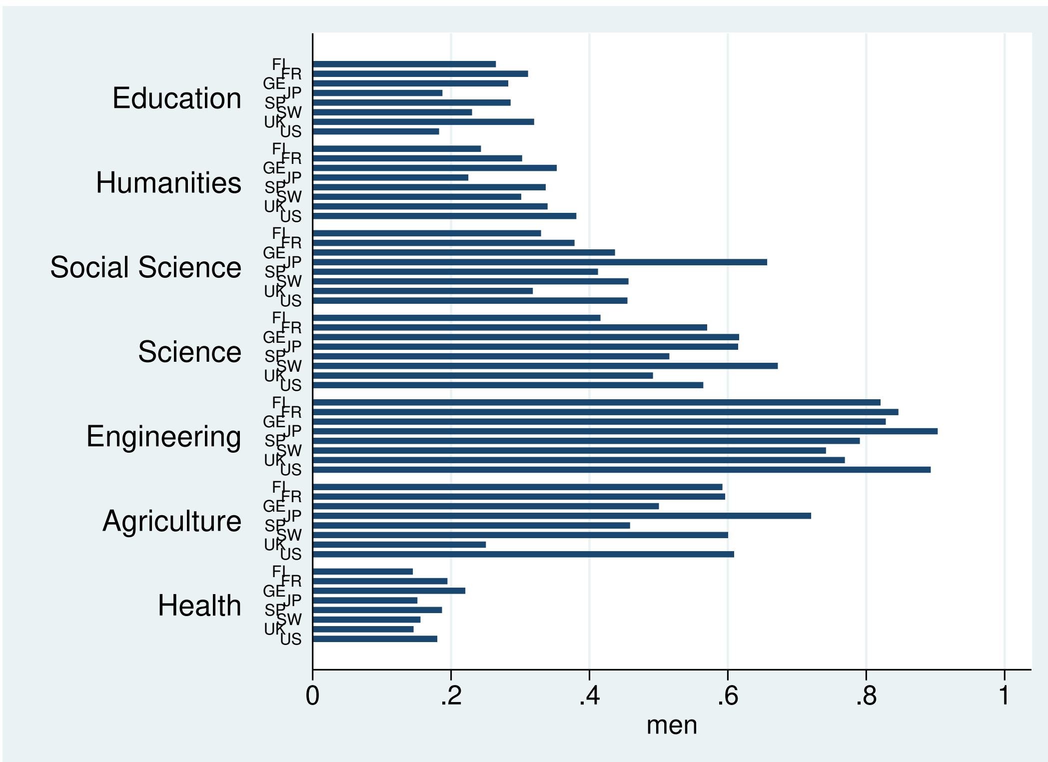


Figure A-3: Share of men in different fields of study by country



FI: Finland; FR: France: GE: Germany; JP: Japan; SP: Spain; SW: Sweden; PIAAC data. Authors' own calculations.

Figure A-4: Value-added share of sectors associated to field of study “Health and Welfare”

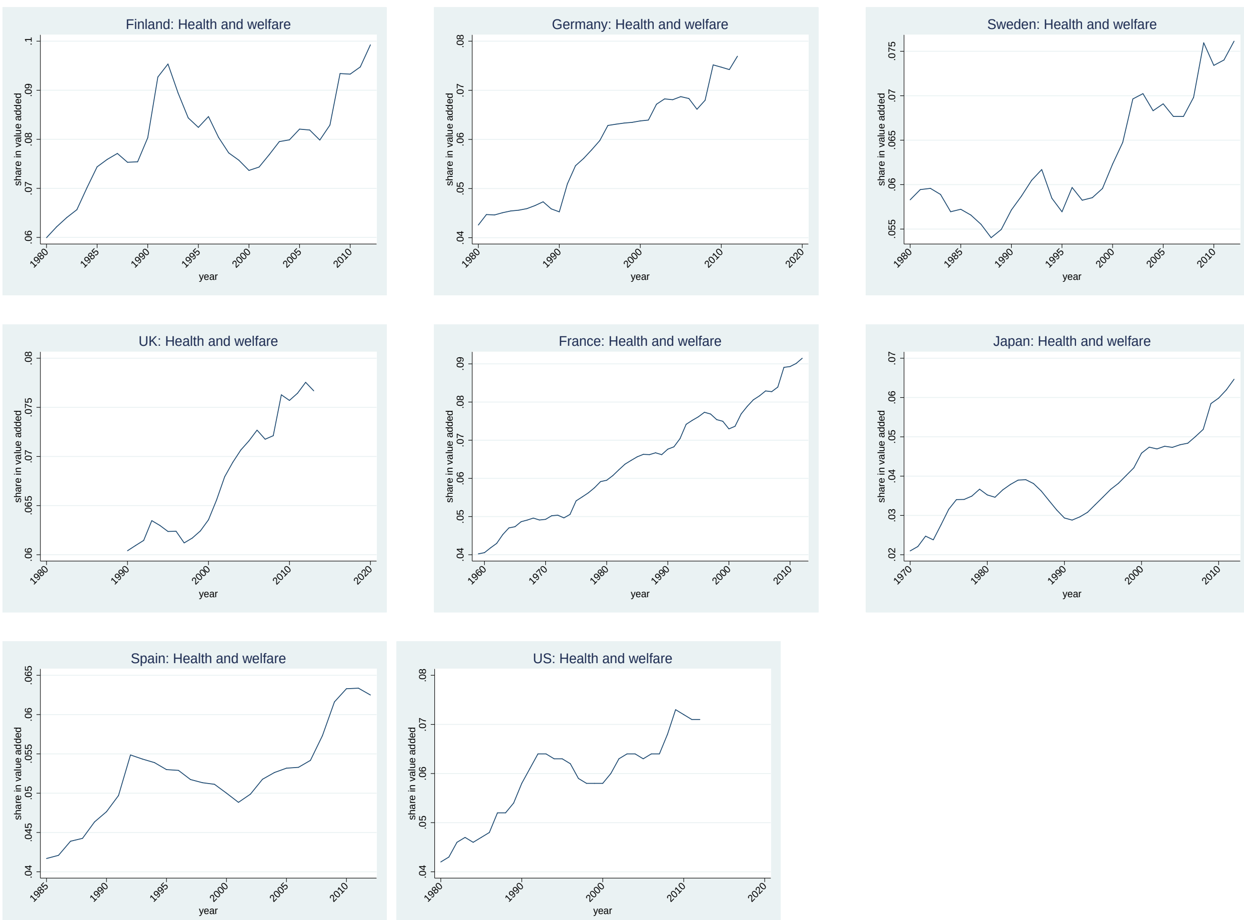


Figure A-5: Value-added share of sectors associated to field of study “Teacher Training and Education Science”

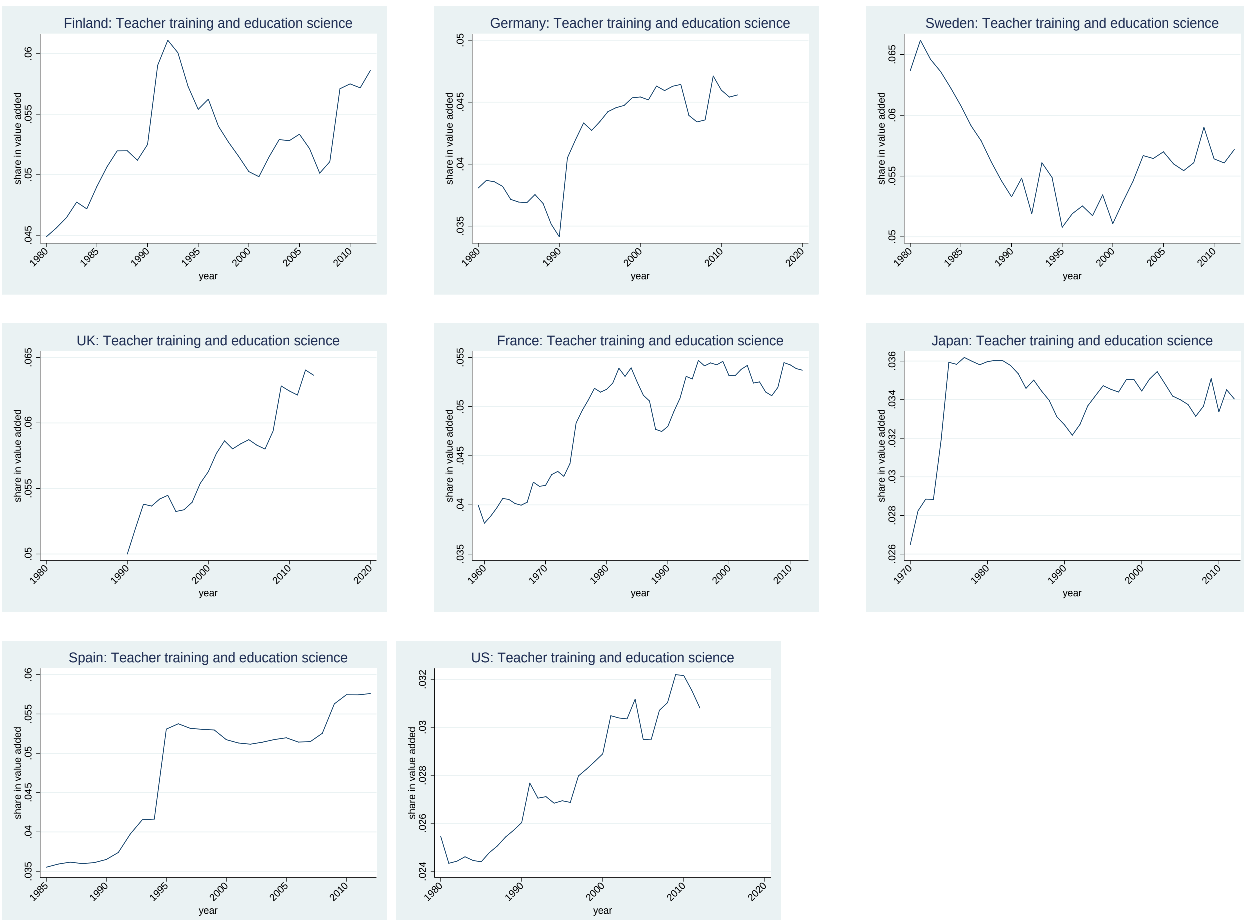
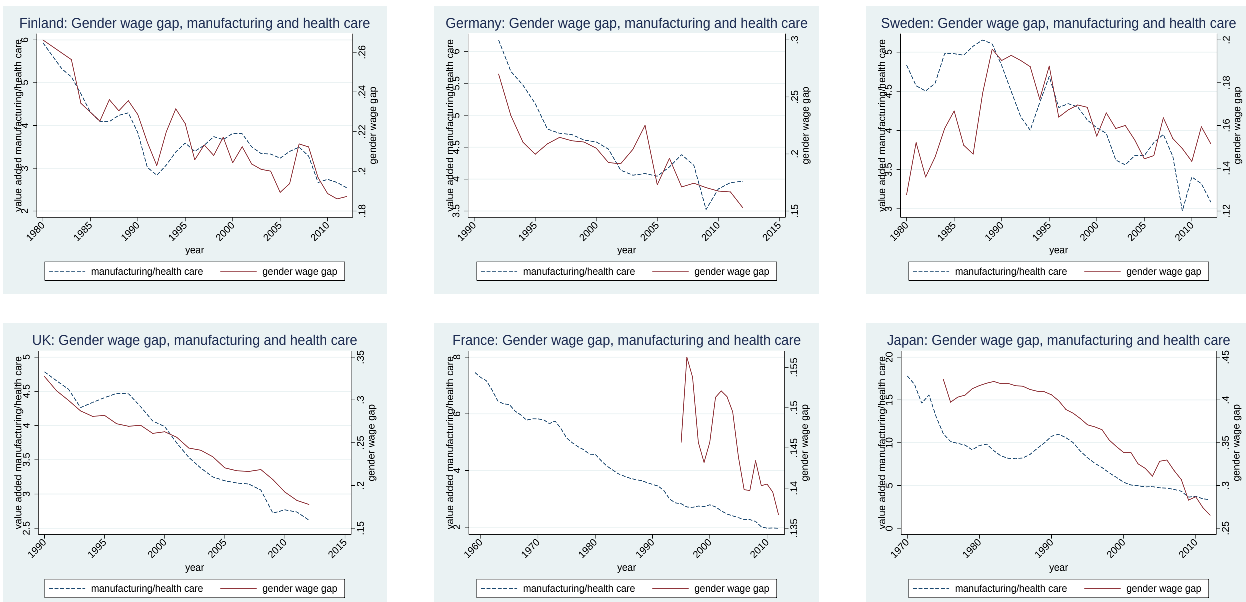
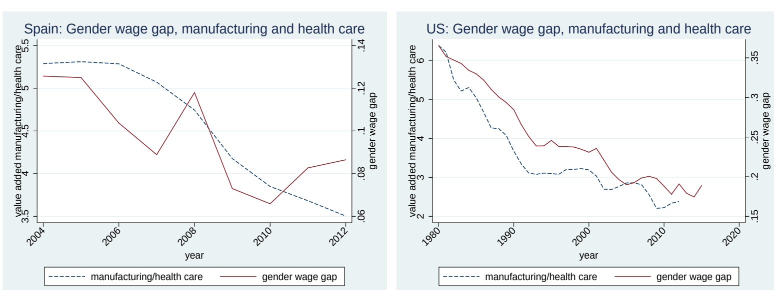


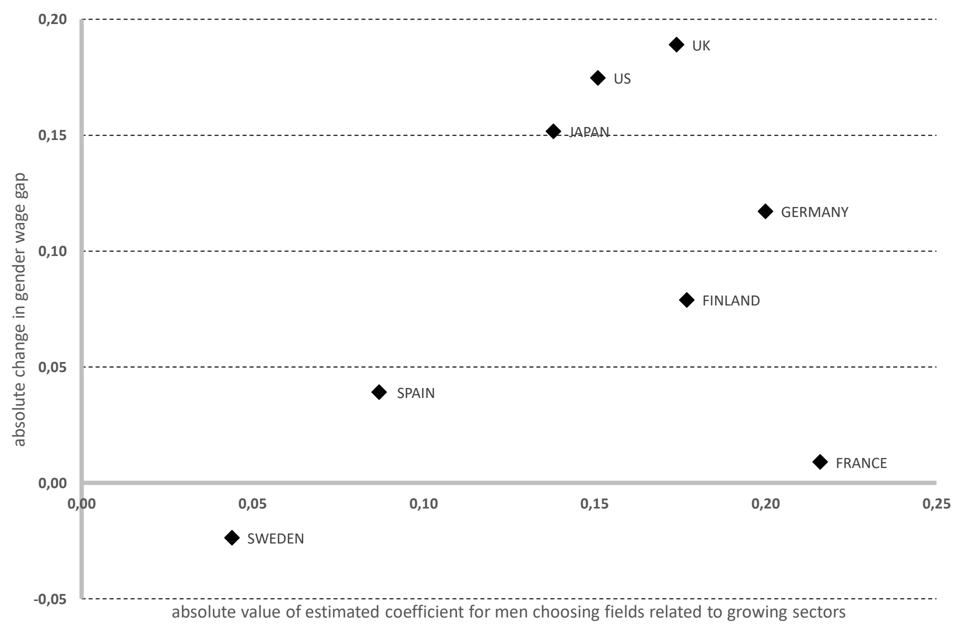
Figure A-6: Gender wage gaps and ratio of value added in manufacturing to health care





Source: OECD for gender wage gaps

Figure A-7: Change in gender wage gap and estimated coefficients for men avoiding fields of study related to growing sectors



OECD data for gender wage gap; estimated coefficients from Table A8.

A.2 Tables

Table A1: Data sources for value added shares by sectors

Country	Source	Main Tables
United States	BEA	Supplemental estimates, Value added by industry, current-dollar shares, 69 Industries
United Kingdom	ONS	GDP(O) Low Level Aggregates 2014 Q1, Month 1
Finland	OECD	Gross value added by activity, current prices
France	INSEE	Base 2010 - Production and operating accounts by branch - level A38 Gross value added all branches - current prices
Germany	Statistisches Bundeamt	VGR de Bundes - Bruttowertschöpfung (nominal/preisbereinigt) Wirtschaftsbereiche
Japan	Statistics Japan	Gross domestic product classified by economic activities (Medium industry group) (At Current Prices, At Constant Prices, Deflators) - 68SNA, benchmark year= 1990
Spain	INE	Valor añadido bruto: precios corrientes 4.1 Cuentas de producción y explotación por ramas de actividad
Sweden	Cabinet Office Statistics Sweden	GDP: production approach (ESA2010), by industrial classification SNI 2007

Table A2: Data sources for additional macroeconomic variables

Variable	Source
% contracts covered by collective bargaining	Visser [2013]
Public expenditure to GDP	
Germany	Statistisches Bundesamt; use of GDP; long series
United Kingdom	ONS; value added of public administration to GDP
United States	BEA; Table 102: Gross Domestic Product (Expenditure Side)
all other countries	World Bank Data
Quarterly real GDP per capita	
Finland	Statistics Finland; per capita: divided by annual population from OECD
France	INSEE; per capita: divided by annual population from same source
Germany	Statistisches Bundesamt; quarterly series for real GDP per capita upon request
Japan	Statistics Japan; growth rates of total real GDP and subtract population growth rates
Spain	INE; growth rates of real GDP (aggregate) and subtract population growth bi-annually
United Kingdom	ONS
United States	St. Louis Federal Reserve

Table A3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
PIAAC data					
Education	0.108	0.310	0	1	10,774
Humanities, Languages, Art	0.116	0.320	0	1	10,774
Social Science, Business, Law	0.288	0.453	0	1	10,774
Science, Maths, Computing	0.109	0.311	0	1	10,774
Engineering, Manufacturing, Construction	0.187	0.390	0	1	10,774
Agriculture,Veterinary	0.024	0.154	0	1	10,774
Health and Welfare	0.169	0.375	0	1	10,774
Finland	0.127	0.333	0	1	10,774
France	0.128	0.334	0	1	10,774
Germany	0.135	0.342	0	1	10,774
Japan	0.135	0.341	0	1	10,774
Spain	0.081	0.273	0	1	10,774
Sweden	0.112	0.316	0	1	10,774
UK	0.134	0.341	0	1	10,774
US	0.147	0.354	0	1	10,774
1980s	0.156	0.363	0	1	10,774
1990s	0.309	0.462	0	1	10,774
2000s	0.535	0.499	0	1	10,774
Vocational degree	0.332	0.471	0	1	10,774
Male	0.442	0.497	0	1	10,774
Foreign born	0.100	0.299	0	1	10,774
Parental education: secondary	0.369	0.483	0	1	10,774
Parental education: tertiary	0.416	0.493	0	1	10,774
Numeracy: Proficiency level 1	0.046	0.209	0	1	10,774
Numeracy: Proficiency level 2	0.217	0.412	0	1	10,774
Numeracy: Proficiency level 3	0.449	0.497	0	1	10,774
Numeracy: Proficiency levels 4 &5	0.279	0.448	0	1	10,774
Readiness to learn 1	0.106	0.308	0	1	10,774
Readiness to learn 2	0.159	0.366	0	1	10,774
Readiness to learn 3	0.207	0.405	0	1	10,774
Readiness to learn 4	0.244	0.430	0	1	10,774
Readiness to learn 5	0.283	0.450	0	1	10,774
Log hourly wage	3.109	0.458	1.524	4.976	8,018
Job experience	12.974	8.118	2	32	10,774
Works in related occupation	0.250	0.433	0	1	10,774
Health: poor or fair	0.100	0.301	0	1	10,766
Has children	0.619	0.486	0	1	10,770
Worked last week	0.809	0.393	0	1	10,774
National statistics: Matched data					
Chose growing field	0.596	0.491	0	1	10,774
Recession	0.121	0.326	0	1	10,774
% contracts collective bargaining	0.602	0.308	0.131	0.945	10,774
Government expenditure/GDP	0.154	0.069	0.049	0.275	10,774

Table A4: Growth in related sectors and choice of field of study

	Eng	Educ	Health	Humanities	Science	Business	Agriculture
$eng - growth_{t-4}$	0.027 (0.013)**						
$eng - growth_{t-3}$	0.006 (0.015)						
$eng - growth_{t-2}$	0.015 (0.012)						
$edu - growth_{t-4}$		0.018 (0.008)**					
$edu - growth_{t-3}$		0.042 (0.009)***					
$edu - growth_{t-2}$		0.028 (0.008)***					
$health - growth_{t-4}$			0.068 (0.01)***				
$health - growth_{t-3}$			-.0008 (0.013)				
$health - growth_{t-2}$			0.056 (0.01)***				
$human - growth_{t-4}$				0.023 (0.01)**			
$human - growth_{t-3}$				0.0007 (0.012)			
$human - growth_{t-2}$				0.024 (0.009)***			
$scie - growth_{t-4}$					0.015 (0.007)**		
$scie - growth_{t-3}$					0.013 (0.008)*		
$scie - growth_{t-2}$					0.03 (0.007)***		
$busin - growth_{t-4}$						0.088 (0.015)***	
$busin - growth_{t-3}$						0.032 (0.019)*	
$busin - growth_{t-2}$						0.049 (0.015)***	
$agri - growth_{t-4}$							-.0007 (0.007)
$agri - growth_{t-3}$							0.004 (0.008)
$agri - growth_{t-2}$							-.008 (0.006)
Number of observations	10,617	10,617	10,617	10,617	10,378	10,617	10,617
R-squared	0.305	0.097	0.212	0.12	0.113	0.259	0.025

The dependent variable is an indicator that takes on value one if in period t individuals chose the field of study Engineering, Education, Health care, Humanities, Science, Business, and Agriculture in columns (1) to (7) respectively. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All regressions include as additional controls a dummy for vocational degree, for male, foreign born, highest parental education being secondary, and highest parental eduction being tertiary. All regressions are estimated by OLS. Heteroskedasticity robust standard errors. Fewer observations for science because assignment of sectors to field of study in US only from 1977 onwards.

Table A5: Specialization in fields of study when related sectors are growing and hourly wages later in life - Heckman selection model

	Full sample		Women	
	log wage	worked last week	log wage	worked last week
growfield_i, t-j	0.027***	-0.005	0.047***	0.007
	(0.010)	(0.032)	(0.013)	(0.041)
Job experience	0.037***	0.044***	0.033***	0.043***
	(0.003)	(0.010)	(0.004)	(0.012)
Experience squared/100	-0.066***	-0.144***	-0.063***	-0.131***
	(0.011)	(0.034)	(0.015)	(0.044)
Vocational degree	-0.209***	-0.166***	-0.173***	-0.091**
	(0.011)	(0.033)	(0.014)	(0.042)
Male	0.162***	0.418***		
	(0.015)	(0.032)		
Foreign born	-0.051***	-0.280***	-0.077***	-0.326***
	(0.019)	(0.049)	(0.024)	(0.061)
Parental education: secondary	0.008	-0.091**	0.011	-0.133**
	(0.013)	(0.042)	(0.017)	(0.052)
Parental education: tertiary	0.029**	-0.157***	0.047***	-0.203***
	(0.014)	(0.043)	(0.018)	(0.054)
Health: poor or fair		-0.459***		-0.410***
		(0.046)		(0.058)
background - children		-0.170***		-0.444***
		(0.035)		(0.044)
Constant	2.776***	0.269	2.649***	0.315
	(0.095)	(0.275)	(0.122)	(0.353)
Observations	9,515	9,515	5,457	5,457

The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All regressions include the same set of controls as those in column 4 of Table 4.

Table A6: Robustness: Specialization in fields of study and related sector growth when individuals were 18 years old and hourly wages later in life

	(1)	(2)	(3)	(4)	(5)	(6)
$growfield_{i,age18}$	0.008 (0.016)	0.028 (0.012)**	0.028 (0.012)**	0.032 (0.011)***	0.035 (0.012)***	0.032 (0.013)**
Male		0.178 (0.011)***	0.176 (0.011)***	0.151 (0.011)***	0.134 (0.011)***	0.132 (0.011)***
Vocational degree		-.238 (0.011)***	-.232 (0.011)***	-.202 (0.011)***	-.231 (0.012)***	-.231 (0.012)***
Job experience		0.038 (0.003)***	0.039 (0.003)***	0.037 (0.003)***	0.038 (0.003)***	0.039 (0.003)***
Experience squared/100		-.074 (0.009)***	-.075 (0.009)***	-.063 (0.013)***	-.066 (0.012)***	-.068 (0.011)***
Foreign born		-.091 (0.02)***	-.092 (0.02)***	-.054 (0.02)***	-.053 (0.02)***	-.058 (0.02)***
Parental education: secondary		0.037 (0.014)***	0.034 (0.014)**	0.028 (0.013)**	0.027 (0.013)**	0.026 (0.013)**
Parental education: tertiary		0.077 (0.014)***	0.073 (0.014)***	0.058 (0.014)***	0.061 (0.014)***	0.062 (0.013)***
Numeracy: Level 2				0.095 (0.029)***	0.102 (0.029)***	0.101 (0.029)***
Numeracy: Level 3				0.168 (0.029)***	0.176 (0.029)***	0.174 (0.029)***
Numeracy: Level 4 & 5				0.252 (0.03)***	0.25 (0.03)***	0.243 (0.03)***
Country FE		x	x	x	x	x
Non-cognitive ability			x	x	x	x
Macroeconomic controls				x	x	x
Decade dummies				x	x	x
Field dummies					x	x
Field-Country dummies						x
Number of observations	6,947	6,947	6,947	6,938	6,938	6,938
R-squared	0.00007	0.268	0.271	0.293	0.311	0.324

The dependent variable are log hourly wages. $growfield_{i,age18}$ is an indicator for having specialized in a field of study when its related sectors were growing when individuals were 18 years old. All macroeconomic controls (recession dummies, % contracts covered by collective bargaining and government expenditure to GDP) are also measured when individuals were 18 years old. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. Columns 1 to 6 are estimated by OLS. Standard errors are clustered by country, field of study, and year.

Table A7: Specialization in fields of study when related sectors are growing and hourly wages later in life - continuous measure for sector growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$growth/VA_{i,t-j}$	0.091 (0.08)	0.15 (0.048)***	0.148 (0.048)***	0.177 (0.047)***	0.101 (0.05)**	0.072 (0.051)	0.067 (0.05)	-.089 (0.06)
Male		0.173 (0.01)***	0.171 (0.01)***	0.148 (0.01)***	0.135 (0.011)***	0.133 (0.011)***	0.127 (0.01)***	0.129 (0.01)***
Vocational degree		-.233 (0.01)***	-.227 (0.01)***	-.200 (0.01)***	-.228 (0.011)***	-.227 (0.011)***	-.225 (0.011)***	-.221 (0.011)***
Job experience		0.037 (0.003)***	0.037 (0.003)***	0.035 (0.003)***	0.036 (0.003)***	0.037 (0.003)***	0.037 (0.003)***	0.038 (0.003)***
Experience squared/100		-.071 (0.009)***	-.072 (0.009)***	-.062 (0.013)***	-.064 (0.012)***	-.067 (0.011)***	-.066 (0.011)***	-.068 (0.011)***
Foreign born		-.092 (0.018)***	-.092 (0.018)***	-.053 (0.018)***	-.054 (0.018)***	-.057 (0.018)***	-.054 (0.018)***	-.053 (0.018)***
Parental education: secondary		0.025 (0.012)**	0.022 (0.012)*	0.015 (0.011)	0.014 (0.011)	0.013 (0.011)	0.012 (0.011)	0.012 (0.011)
Parental education: tertiary		0.059 (0.012)***	0.056 (0.012)***	0.037 (0.012)***	0.04 (0.012)***	0.042 (0.012)***	0.043 (0.012)***	0.042 (0.012)***
Numeracy: Level 2				0.106 (0.025)***	0.109 (0.025)***	0.108 (0.025)***	0.104 (0.025)***	0.101 (0.025)***
Numeracy: Level 3				0.177 (0.025)***	0.183 (0.024)***	0.181 (0.025)***	0.176 (0.025)***	0.174 (0.025)***
Numeracy: Level 4 & 5				0.258 (0.026)***	0.254 (0.026)***	0.246 (0.027)***	0.24 (0.027)***	0.238 (0.027)***
Works related occupation							0.108 (0.013)***	0.099 (0.012)***
$growth/VA_{i,t-j}$ ×works related								0.575 (0.105)***
Country FE		x	x	x	x	x	x	x
Non-cognitive ability			x	x	x	x	x	x
Macroeconomic controls				x	x	x	x	x
Decade dummies				x	x	x	x	x
Field dummies					x	x	x	x
Field-Country dummies						x	x	x
Number of observations	8,018	8,018	8,018	8,018	8,018	8,018	8,018	8,018
R-squared	0.0004	0.265	0.268	0.287	0.305	0.319	0.326	0.329

The dependent variable are log hourly wages. $growth/VA_{i,t-j}$ indicates the 5-year percentage point change in the value added share relative to the initial value added share. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All columns are estimated by weighted OLS.

Table A8: Individual characteristics related to specializing in growing fields of study - by country

	fin	fra	ger	jpn	esp	swe	uk	us
Male	-.177 (0.053)***	-.216 (0.037)***	-.200 (0.045)***	-.138 (0.046)***	-.087 (0.038)**	-.044 (0.041)	-.174 (0.043)***	-.151 (0.041)***
Vocational degree	0.015 (0.031)	-.080 (0.045)*	0.014 (0.048)	-.030 (0.056)	-.111 (0.071)	-.073 (0.051)	-.070 (0.065)	-.106 (0.052)**
Foreign born	0.02 (0.075)	-.060 (0.039)	-.076 (0.042)*	0.007 (0.261)	0.018 (0.055)	0.01 (0.043)	-.084 (0.038)**	-.133 (0.039)***
Numeracy: Level 4 & 5	-.119 (0.081)	-.239 (0.056)***	0.065 (0.073)	-.122 (0.099)	-.045 (0.09)	-.128 (0.085)	-.069 (0.06)	-.028 (0.045)
Number of observations	1,373	1,378	1,457	1,452	872	1,208	1,448	1,586
R-squared	0.152	0.103	0.065	0.073	0.047	0.022	0.058	0.067

The dependent variable is $growfield_{i,t-j}$, an indicator for having specialized in a field of study when its related sectors were growing. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All regressions are estimated by OLS and include the full set of controls (see column 6 of Table 5). Heteroskedasticity robust standard errors clustered by country, field of study and year.

Table A9: Robustness Check: Determinants of specializing in fields of study - controlling for graduates after last economic crisis

	(1)	(2)
Male	-.155	-.160
	(0.016)***	(0.018)***
Graduated after 2008	0.015	0.003
	(0.052)	(0.054)
Male×Grad aft. 2008		0.029
		(0.04)
Vocational degree	-.048	-.049
	(0.018)***	(0.018)***
Foreign born	-.054	-.054
	(0.017)***	(0.017)***
Numeracy: Level 4 & 5	-.078	-.078
	(0.024)***	(0.024)***
Number of observations	10,774	10,774
R-squared	0.073	0.073

The dependent variable is $growfield_{i,t-j}$, an indicator for having specialized in a field of study when its related sectors were growing. The coefficients are marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All regressions are estimated by OLS and include the full set of controls (see column 6 of Table 5). Heteroskedasticity robust standard errors clustered by country, field of study and year of study.

Table A10: Men's decision to specialize in growing female, growing male, or growing neutral (Social Science, Business & Law) fields compared to choosing non-growing fields by degree type

	Bachelor's degree or higher	Vocational degree
Estimated coefficients for "Male" choosing the following categories		
Growing female field	-1.058***	-2.031***
	(0.0793)	(0.132)
Growing male field	0.370***	0.301*
	(0.114)	(0.173)
Growing SSBL	-0.292****	-1.066***
	(0.0770)	(0.140)

Coefficients from multinominal logit regression marked with * if the level of significance is between 5% and 10%, ** if the level of significance is between 1% and 5% and *** if the level of significance is less than 1%. All columns are estimated by multinominal logit regression of the following categorical variable: 1: chose non-growing field, 2: chose female growing field, 3: chose male growing field and 4: chose SSBL growing. Baseline category is 1. They all include the same controls as those in column 6 of Table 5. Robust standard errors clustered by country, field of study and year of study.

Table A11: Summary statistics: Men's and Women's choice of fields of study - growing/shrinking; female or SSBL - for selected countries

Variable	**Mean**
Finland	
Women	
$growfield_{t-j}$	0.526
Social Science Business and Law	0.304
Growing SSBL	0.189
Men	
Female field of study	0.186
Japan	
Women	
$growfield_{t-j}$	0.560
Social Science Business and Law	0.151
Growing SSBL	0.136
Men	
Female field of study	0.181
Sweden	
Women	
$growfield_{t-j}$	0.588
Social Science Business and Law	0.240
Growing SSBL	0.099
Men	
Female field of study	0.199
UK	
Women	
$growfield_{t-j}$	0.660
Social Science Business and Law	0.386
Growing SSBL	0.307
Men	
Female field of study	0.279
US	
Women	
$growfield_{t-j}$	0.787
Social Science Business and Law	0.286
Growing SSBL	0.270
Men	
Female field of study	0.236