Specializing in growing sectors: Wage returns and gender differences

Graves, Jennifer; Kuehn, Zoë

Labour Economics 70 (2021) 101994

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

Specializing in growing sectors: Wage returns and gender differences[☆]

Jennifer Graves, Zoë Kuehn[*]

Universidad Autónoma de Madrid, Madrid 28049, Spain

ARTICLE INFO

JEL classification:
I21
I23
J24
J16
O57

Keywords:
Higher education
Specialization
Sectors
Wages
Gender
PIAAC

ABSTRACT

Matching individual data with national statistics for eight high-income OECD countries, we test whether those who specialized in fields of study when related sectors were growing earn higher wages later in life. 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 but when related sectors were not growing. We then test for heterogeneity in both who chooses fields of study associated with growing sectors, as well as in the wage impacts of doing so. We find that men are less likely to specialize in growing fields because they avoid traditionally female fields that have grown more over recent decades (i.e. health care and 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. Countries where men are less likely to specialize in growing fields are characterized by more traditional gender norms but also larger reductions in gender wage gaps.

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 et al. (2012) or Altonji et al. (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 et al. (2012); Arcidiacono (2004)). Surprisingly, little is known about the joint effects of economic conditions and specialization decisions on earnings.[1]

The current paper tests whether individuals who specialized in fields of study when related sectors were growing earn higher wages later in life. To this end, we match individual data with national statistics for eight high-income OECD countries. We then compare individuals of similar characteristics and abilities who made their specialization choices under comparable macroeconomic conditions but at different times. Those who specialized in fields of study when related sectors were growing earn 2-3% higher hourly wages in 2011 (on average, roughly a decade after graduation). We also find that these positive wage effects are driven by those who later work in occupations related to their field of study. Indeed, for these individuals the effects are much larger; 6-7% higher hourly wages.

We then test for heterogeneity in both who chooses fields of study associated with growing sectors, as well as in the wage impacts of doing so. We find men to be less likely to specialize in growing fields, because they avoid traditionally female fields whose related sectors have grown more over recent decades (i.e. health care and 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, for men with vocational degrees we do not find the

☆ This paper is part of a research project funded by the Fundación Ramón Areces within their 13th Social Science National Competition 2014. We also acknowledge financial support from the Spanish Ministry of Science and Innovation (grant ECO2017-82882-R) as well as funding from Comunidad de Madrid (grant SI1-PJ1-2019-00326). We would like to thank participants at seminars at Universidad Autónoma de Madrid and Universidad Complutense de Madrid as well as the AEFP meetings 2018 and the COSME workshop 2019 for useful comments and suggestions. We are also very grateful to Ainoa Aparicio Fenoll, Eva García-Morán, Nick Huntington-Klein, and Jan Stuhler for providing valuable feedback.

* Corresponding author.
E-mail addresses: jennifer.graves@uam.es (J. Graves), zoe.kuehn@uam.es (Z. Kuehn).

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

https://doi.org/10.1016/j.labeco.2021.101994
Received 19 May 2020; Received in revised form 14 April 2021; Accepted 15 April 2021
Available online 20 April 2021
0927-5371/

same result, and hence non-wage factors must drive their reluctance towards female fields (e.g. gender identity as suggested by Akerlof and Kranton (2000)).

Exploring differences in our findings across countries, we find more traditional gender norms but larger reductions in gender wage gaps in countries where men are more reluctant to specialize in growing fields. We also show that gender differences in specialization choices together with our estimates for wage returns to specializing in growing fields 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 between 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' field of study and year of graduation, we match PIAAC data to national statistics on value-added of related sectors. We then determine whether related sectors were growing or shrinking at the moment individuals chose their field of study. For robustness, we also construct an alternative measure based on growth in employment instead of value added.

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 additional macroeconomic conditions – business cycle, government spending, strength of unions – at the time students made their specialization choices to account for the possibility that for instance 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 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]

There are reasons to think that sector-specific economic conditions might impact men's and women's specialization decisions differently. On the one hand, most studies indicate that male students take expected earnings more into consideration than female students when making specialization decisions (e.g. Zafar (2013), Long et al. (2015), Montmarquette et al. (2002)). At first glance, our results on the positive wage effect of choosing growing fields together with men being less likely to specialize in growing fields, seem to stand in contrast to these findings. However, fields of study are also notably segregated by gender, and this is quite persistent over time. In all countries in our sample, men are much more likely than women to specialize in engineering whereas they are much less likely to choose fields such as education or health care which have grown more over recent decades.

In line with this observation, whereas most literature finds that 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)), more 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 et al. (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 role 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 et al. (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.

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). We can thus analyze the wage impact as well as the determinants of choice of field of study for all individuals for whom specialization decisions matter for future labor market outcomes, and we are able to study potential differences in outcomes and decisions across degree types.

Finally, few studies on the effect of economic conditions on education decisions and labor market outcomes consider countries other than the United States.[5] Using PIAAC data, available for different countries, we contribute to this literature with a multi-country analysis which enables us to relate our findings to cross-country differences in gender norms and the evolution of the gender wage gap.

The remainder of this paper is organized as follows: In Section 2 we describe our data and we present descriptive evidence for our variable of growth in related sectors and show that it is a meaningful predictor for labor market opportunities in different fields of study. Section 3 presents our main estimation of wage effects of specializing in fields of study when related sectors are growing. In Section 4 we test for heterogeneity. Section 5 explores differences in our results by country, discussing the role of gender norms and the implications of our results for the gender wage gap. Section 6 concludes.

2. Data

Our main dataset combines individual data from PIAAC with national statistics on value added of sectors. For our analysis we focus on

[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 et al. (2016)). However, unlike most of this literature the current paper does not model individuals' specialization choices.

[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 et al. (2019)).

[5] For some of the few examples see Aina et al. (2011) for Italy, Messer and Wolter (2010) for Switzerland, Beffy et al. (2012) for France, and Aparicio Fenoll (2016) for Spain.

the following eight countries: Finland, France, Germany, Japan, Spain, Sweden, the UK, and the US.[6]

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.[7]

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.[8] Second, we have information on individuals' highest level of education (ISCED: 0 to 6).[9] Since fields of study are not particularly meaningful at lower levels of education, we restrict our sample to individuals aged 20–65 with post-secondary education including university as well as vocational degrees (ISCED 4B or above).[10] 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.[11] 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 merge data from national statistics on value added of related sectors in the year each individual was most likely to have made their 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 lags for each country. To define them we relied on sources such as typical moments for declaring a major at top universities as well as official guidelines for the duration of studies.[12] 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' current occupation 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 occupations that are not matched to any of the seven fields 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

A primary data challenge in this paper is to create an indicator for whether sectors related to a field of study were growing when indi-

[6] 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. 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.

[7] 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.

[8] 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.

[9] 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.

[10] We are unable to further differentiate between undergraduate and graduate studies because PIAAC only provides this information for some but not all countries in our sample.

[11] 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.

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

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."

viduals made their specialization choices. Given that we consider individuals who graduated between 1980 and 2010, we need data that allows us to check whether in their year of specialization, i.e. 2, 3, or 4 years before graduation, sectors had been growing. Our benchmark estimation considers growth over the past five years, and hence ideally our time series starts in 1971. The data also has to be available for all eight OECD countries. Only national accounts data on value added or employment by sector fulfills these two requirements.[13] While a priori it is unclear which measure – value added or employment – provides a better reflection of labor market opportunities for individuals with post-secondary degrees, we prefer value added for two reasons: i) changes in employment could be driven by individuals with lower levels of education, in particular considering the strong decline in manufacturing employment and the increase in automation in this sector, and ii) as long as labor shares within sectors are relatively constant, changes in value added shares reflect changes in earnings potential.[14] Nonetheless, we run robustness checks using growth in employment to show that this choice does not notably alter our findings.

For the United States we have data on value added 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 by sectors is 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 public education by a fraction of government's value added equal to the share of education in public expenditure.[15] 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 A-1 in the Appendix). Further details as well as the correspondences between sectors and fields of study for these countries are presented in the Companion Appendix.

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

[13] While there are many potential ways to measure sector growth over time, the problem with alternative measures lies with their availability and comparability over time. For example, a measure such as open vacancies by sector as provided by JOLTS in the US is only available from 2001.

[14] 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 of growing sectors with wage growth experienced by individuals with post-secondary degrees.

[15] 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.

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, and we include government expenditure to GDP to reflect changes in public employment opportunities. As mentioned before, for robustness checks we also construct an indicator for growth in employment shares of related sectors; see Table A-1 in the Appendix for the sources of these additional variables.

2.3. Matched data

For each of the seven fields of study, we first calculate the change in the value added share of related sectors over 5 years.[16] 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, our assignment of sectors to fields of study is imperfect and hence to reduce measurement error, our preferred specification uses the dummy variable instead of the continuous variable.

Table 3 displays the summary statistics for our sample.[17] Our main sample consists of 10,774 individuals, and we have wage information for 8,018 individuals. The most common field of study is social science, business and law (29%), and each country is roughly similarly represented in our sample. Around 10% of all individuals made their specialization choice before 1985 and 40% after 2000. Approximately one third holds 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.[18] For cognitive skills we use proficiency levels in numeracy as defined by PIAAC.[19] 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.

Fig. 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 was slightly more prevalent during the late seventies and early eighties. 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.

As mentioned before, our sample only includes individuals aged 20–65 with post-secondary degrees in fields of study which we can assign to sectors. Given cross-country differences in educational attainment, in each country our sample represents distinct shares of the overall population. While percentages of individuals with university versus vocational degrees also vary across countries, the inclusion of both types of degrees means that this does not impact sample selection. Compared to the overall PIAAC data, individuals in our sample are more educated, have higher numeracy and non-cognitive skills, their parents tend to be more educated, they have higher wages, and report to be healthier. The share of individuals in higher education specializing in the excluded fields "general programmes" and "services" varies across countries (between 5% and 20%), and hence our sample is more restrictive in some countries compared to others. However, given that we cannot map these fields to specific sectors, we acknowledge that, while our results do not apply to all individuals with higher education, they do speak for the vast majority of the population with post-secondary education in the eight countries in our sample.

2.4. Descriptive evidence: growing sectors

Before estimating the wage effects of choosing a growing field, we provide descriptive evidence for our variable of growth in value added of related sectors, and we show that it is a meaningful predictor for labor market opportunities in different fields of study.

Fig. 1 displays the evolution of value added and employment shares for the seven fields of study for the United States. Value added and employment shares of sectors related to education, health and welfare, and social science increased over the time period considered while they decreased in 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 went into education in 2005. We observe considerable variation both within and across countries in the timing of periods of growth or decline of sectors (see Figs. A-3–A-9 in the Appendix). We also observe close correlations between value added and employment shares.[20] While for the reasons previously discussed, we believe growth in value-added shares to be a better measure for labor market opportunities for individuals with post-secondary degrees, we also repeat our regression analysis using employment shares. Our main results are maintained (see Tables A14-A16 in the Companion Appendix).

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 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. Note that for this regression we assume the maximum lag between individuals' decision years and graduation; i.e. 4 years. In Table A-2 in the Appendix we report the results using two samples. The macro data includes one observation per year and field of study, while the merged PIAAC data includes more observations in years when more individuals in our sample were studying. Our estimated coefficients for the macro data (PIAAC 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 years later is 72.8% (70.9%), compared to 29.2% (38.1%) for fields that were not growing. This difference of 43.6 (32.8) percentage points is roughly equal to 1.5 (0.9)

[16] Our main results are robust to alternative lengths for cumulative growth rates (3, 4, 6, 7 years); see Tables A18-A22 in the Companion Appendix.

[17] For descriptive statistics by country see Table A13 in the Companion Appendix.

[18] 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)).

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

[20] For some countries, including the US, the correlation between growth in value added and employment is quite low for "Humanities" (all years) and "Science" (only later years). This is most likely due to differences in the definitions of sectors between the two variables related to internet and computing, which changed dramatically over the sample years.

Table 3
Summary statistics.

PIAAC data					
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Individual characteristics			*Field of Study*		
Male	0.442	0.497	Education	0.108	0.310
Foreign born	0.100	0.299	Humanities	0.116	0.320
Parental educ.: secondary	0.369	0.483	Social Science	0.288	0.453
Parental educ.: tertiary	0.416	0.493	Science	0.109	0.311
Health: poor or fair*	0.100	0.301	Engineering	0.187	0.390
Has children**	0.619	0.486	Agriculture	0.024	0.154
Vocational degree	0.332	0.471	Health Care	0.169	0.375
Countries			*Year of specialization*		
Finland	0.127	0.333	1977–1989	0.044	0.205
France	0.128	0.334	1980–1984	0.067	0.251
Germany	0.135	0.342	1985–1989	0.117	0.321
Japan	0.135	0.341	1990–1994	0.157	0.364
Spain	0.081	0.273	1995–1999	0.214	0.41
Sweden	0.112	0.316	2000–2004	0.235	0.424
UK	0.134	0.341	2005-2008	0.165	0.372
US	0.147	0.354			
Numeracy skills			*Non-cognitive skills*		
Level 1	0.046	0.209	Readiness to learn 1	0.106	0.308
Level 2	0.217	0.412	Readiness to learn 2	0.159	0.366
Level 3	0.449	0.497	Readiness to learn 3	0.207	0.405
Levels 4 or 5	0.279	0.448	Readiness to learn 4	0.244	0.430
			Readiness to learn 5	0.283	0.450
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	
Labor market variables					
Log hourly wage***	3.109	0.458	1.524	4.976	
Job experience	12.974	8.118	2	32	
Works in related occupation	0.250	0.433	0	1	
Worked last week	0.809	0.393	0	1	
National statistics					
Chose growing field	0.596	0.491	0	1	
Recession	0.121	0.326	0	1	
% contracts collective bargaining	0.602	0.308	0.131	0.945	
Government expenditure/GDP	0.154	0.069	0.049	0.275	

Number of observations: 10,774; *10,766.** 10,770; ***8,018.

times the baseline probability. Note that over time the predictive power of sector growth at specialization decays.[21]

Finally, 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 a regression for our pooled sample for each of the seven fields of study. Table A-3 in the Appendix displays the results. With the exception of the relatively 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.

3. 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,

$$w_i = \alpha_0 + \alpha_1 growfield_{i,t-j} + \alpha_2 Z_i + \alpha_3 VD_i + \alpha_4 x_i + \alpha_5 x_i^2 + \alpha_6 C_{c,t-j} + \alpha_7 D_{5Y,t-j} + \alpha_8 D_c + \epsilon_{i,c,t,t-j}, \quad (1)$$

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 (recession dummy, government spending, union strength) measured at the time of specialization, $D_{5Y,t-j}$ and D_c are year of specialization in five-year categories 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-specialization 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 specializing within the same five years, and 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 5-year 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 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

[21] Using the macro data (PIAAC data) it falls to 1.04 (0.5) times the baseline probability one year later and 0.9 (0.4) times 2 years later.

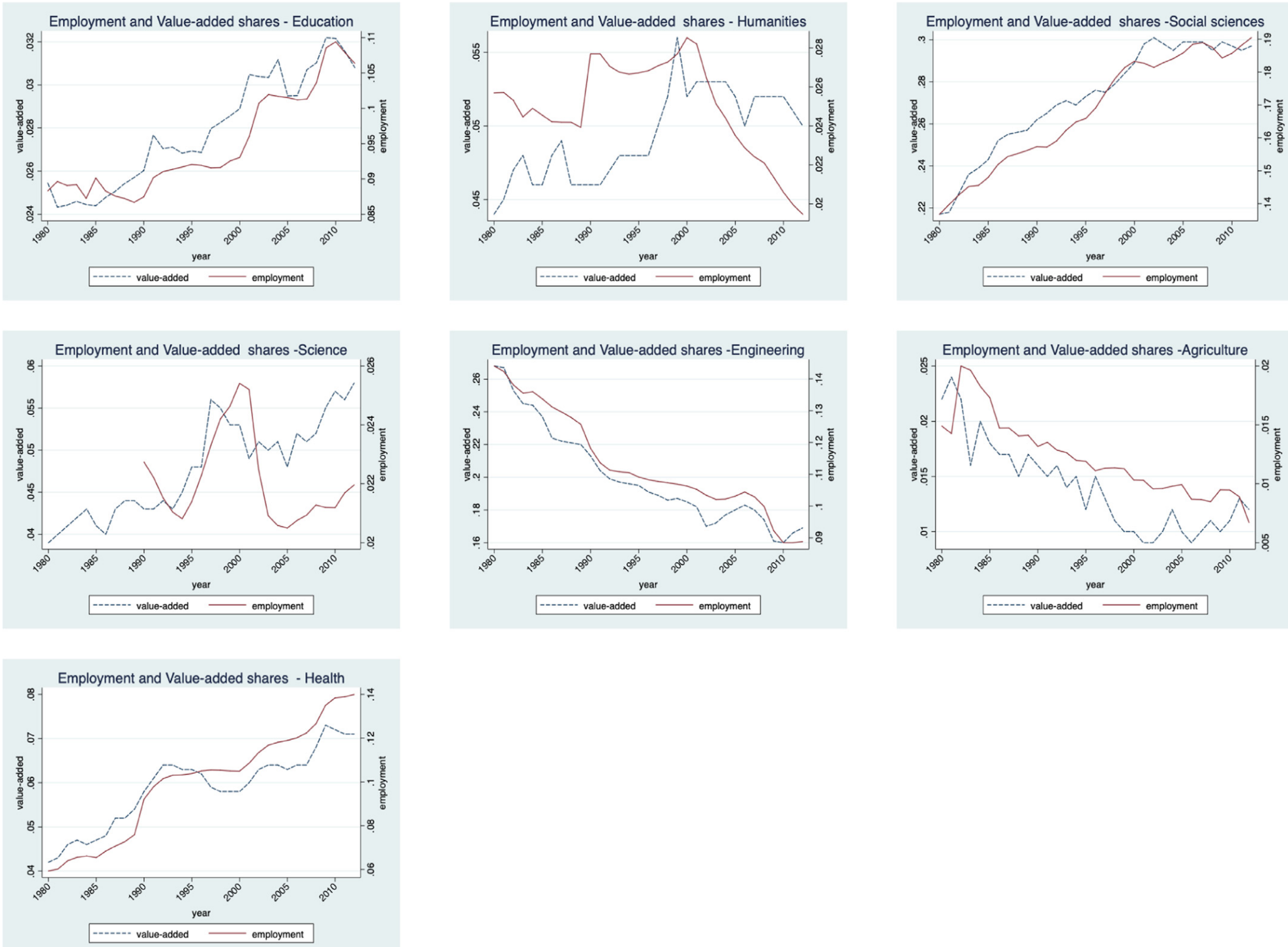

Fig. 1. Value-added and employment shares, United States.
Data sources: BEA and BLS; for further details see the Companion Appendix.

same spirit as is typically used in estimations of wage effects of graduating in recessions.

3.1. Results

Table 4 presents our estimation results. Column 1 only controls for country fixed effects, and in column 2 we add individual controls including measures for non-cognitive and cognitive ability. In column 3 we add macroeconomic controls and 5-year dummies for year of specialization. Column 4 adds field dummies. Finally, in the most demanding specification, column 5 includes also 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. When including field fixed effects the coefficient drops from 0.029 to 0.021, indicating that wage levels in different fields 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 column 6 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 positive wage effect of choosing growing fields operates through individuals working in occupations related to their specialization. Indeed for these individuals the effect is much larger; 6-7% higher hourly wages.

We test the robustness of our results along various dimensions. Instead of controlling for individuals' year of specialization we use the year when individuals were 18 years old, and we also measure macroeconomic controls in that year. Our results remain robust (see Table A-4 in the Appendix). We also estimate Heckman selection models with poor or fair health and having children as exclusion restrictions. Table A-5 in the Appendix shows that controlling for selection into employment, wage effects of specializing in fields related to growing sectors are in line with those in our main estimation, and they are significantly higher

Table 4
Wage impact of aligning post-secondary specialization with growing sectors.

	(1)	(2)	(3)	(4)	(5)	(6)
$growfield_{i,t-j}$	0.011	0.027	0.029	0.02	0.019	−.00005
	(0.014)	(0.01)**	(0.01)***	(0.01)**	(0.01)*	(0.011)
Male		0.147	0.148	0.135	0.133	0.128
		(0.01)***	(0.01)***	(0.011)***	(0.01)***	(0.01)***
Vocational degree		−.200	−.201	−.229	−.228	−.224
		(0.011)***	(0.011)***	(0.012)***	(0.012)***	(0.012)***
Job experience		0.036	0.048	0.05	0.051	0.051
		(0.002)***	(0.008)***	(0.007)***	(0.006)***	(0.006)***
Experience squared/100		−.067	−.102	−.106	−.109	−.110
		(0.008)***	(0.025)***	(0.023)***	(0.021)***	(0.021)***
Foreign born		−.051	−.052	−.053	−.057	−.054
		(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***
Parental education: secondary		0.013	0.014	0.013	0.012	0.012
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Parental education: tertiary		0.036	0.037	0.041	0.042	0.042
		(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***
Numeracy: Level 2		0.105	0.104	0.108	0.108	0.102
		(0.025)***	(0.025)***	(0.025)***	(0.025)***	(0.025)***
Numeracy: Level 3		0.177	0.175	0.182	0.18	0.174
		(0.024)***	(0.024)***	(0.024)***	(0.024)***	(0.024)***
Numeracy: Level 4 or 5		0.258	0.256	0.253	0.246	0.239
		(0.027)***	(0.026)***	(0.027)***	(0.027)***	(0.027)***
Works in related occupation						0.069
						(0.017)***
$growfield_{i,t-j}$×works related						0.066
						(0.02)***
Country FE	x	x	x	x	x	x
Non-cognitive ability		x	x	x	x	x
Macroeconomic controls			x	x	x	x
Year of specialization (5 year bins)			x	x	x	x
Field dummies				x	x	x
Field-Country dummies					x	x
Number of observations	8,018	8,018	8,018	8,018	8,018	8,018
Adjusted R-squared	0.1	0.283	0.284	0.302	0.313	0.321

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.

for women.[22] 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. Table A-6 in the Appendix shows that our results are robust, with the exception of the most demanding specification, reported in column 5, including both field and field-by-country fixed effects. In this case the estimated coefficient falls short of significance at conventional levels (with a p-value of 0.156).

4. Heterogeneity

To better understand the mechanisms behind our results on the positive wage effects of choosing growing fields, we test for heterogeneity in both who chooses fields of study associated with growing sectors, as well as in the wage impacts of doing so.

4.1. Who chooses growing sectors?

We run the following regression to test who chooses growing sectors

$$growfield_{i,t-j} = \beta_0 + \beta_1 Z_i + \beta_2 VD_{i,t} + \beta_3 C_{c,t-j} + \beta_4 D_{5Y,t-j} + \beta_5 D_c + \beta_6 D_f + \epsilon_{i,c,t,t-j}. \quad (2)$$

All variables are as defined before. Our coefficients of interest are β_1 and β_2 on individual characteristics and the indicator variable for vocational degree, respectively. Table 5 presents the results. 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 4), 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 growing fields. Notably, when introducing field fixed effects (in column 5), the coefficient for male becomes insignificant, indicating that men being less likely to choose growing fields is a field-specific phenomenon.

[22] An alternative approach to addressing missing wage information for those not working is to assign them a zero log wage. Our results are robust to repeating our wage regression with this adjusted wage variable, and including a dummy variable for missing wage information, see Table A23 in the Companion Appendix.

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

	(1)	(2)	(3)	(4)	(5)
Male	−.156	−.150	−.154	−.103	−.006
	(0.016)***	(0.016)***	(0.016)***	(0.016)***	(0.01)
Vocational degree		−.039	−.041	0.026	−.011
		(0.017)**	(0.016)***	(0.019)	(0.013)
Foreign born		−.055	−.054	−.054	−.029
		(0.017)***	(0.017)***	(0.017)***	(0.015)**
Parental education: secondary		−.015	−.004	−.005	0.002
		(0.014)	(0.013)	(0.013)	(0.012)
Parental education: tertiary		−.010	0.005	0.005	0.005
		(0.015)	(0.014)	(0.014)	(0.013)
Readiness to learn 2		0.021	0.022	0.021	0.011
		(0.019)	(0.019)	(0.019)	(0.017)
Readiness to learn 3		−.002	−.001	−.002	−.006
		(0.019)	(0.019)	(0.019)	(0.017)
Readiness to learn 4		0.012	0.016	0.014	0.013
		(0.02)	(0.019)	(0.019)	(0.017)
Readiness to learn 5		0.025	0.029	0.027	0.016
		(0.02)	(0.019)	(0.019)	(0.017)
Numeracy: Level 2		−.032	−.029	−.023	−.020
		(0.022)	(0.022)	(0.021)	(0.019)
Numeracy: Level 3		−.040	−.035	−.026	−.016
		(0.021)*	(0.021)*	(0.021)	(0.019)
Numeracy: Level 4 or 5		−.082	−.076	−.070	−.028
		(0.024)***	(0.024)***	(0.023)***	(0.02)
Male×Vocational				−.153	
				(0.026)***	
Country FE	x	x	x	x	x
Macroeconomic controls			x	x	x
Year of specialization (5 year bins			x	x	x
Field dummies					x
Number of observations	10,774	10,774	10,774	10,774	10,774
Adjusted R-squared	0.055	0.058	0.069	0.074	0.244

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 $t-j$.

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 A-7 in the Appendix). Our results 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 results are not driven by the economic and related construction crisis of 2008 which affected men more than women. In Table A-8 in the Appendix we add a dummy variable for specializing after 2008, as well as an interaction term with male to our main regression. The coefficient for men remains largely unchanged.

We also check whether a mismatch of fields to sectors could be driving our results. In particular, sectors related to engineering, manufacturing and construction saw a steady decline over the past decades in every country in our sample (see Figs. A-3–A-9 in the Appendix). However, an engineering degree, especially at the university level may also serve as a general signal for ability (also argued in Blom et al. (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.[23] We then re-estimate Eq. (4.1). Column 1 of Table A-9 in the Appendix presents the results. In column 2, the reassignment of fields of study to sectors is limited to university graduates in engineering who also have high numeracy skills. The coefficient of interest remains negative and highly significant but is somewhat smaller.

The contrast between specifications with and without field fixed effects in Table 5 suggests that while men are 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.

4.2. Genderedness of growing fields

Fields of study are typically very segregated by gender. For the countries in our sample Fig. A-2 in the Appendix shows that men are over-represented in engineering, manufacturing and construction, agriculture and veterinary, and science, math and computing, while they are under-represented 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 these fields, we construct a variable with four categories (k): 1: chose non-growing field, 2: chose female growing field, 3: chose male growing

[23] While also students majoring in science, maths, and computing might go into finance, this sector has not seen a decline similar to engineering, and hence any mismatch would not be driving the result of men being less likely to choose growing fields.

Table 6
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***	−1.637***	−1.546***	−1.678***	−1.669**	−1.119***	−1.329***	−1.024***	−1.436***
	(0.0755)	(0.245)	(0.197)	(0.188)	(0.223)	(0.200)	(0.211)	(0.203)	(0.229)
Growing male field	0.355***	0.512	−0.272	0.484	0.591	0.574*	0.933***	0.177	0.0297
	(0.103)	(0.415)	(0.208)	(0.328)	(0.557)	(0.331)	(0.194)	(0.392)	(0.254)
Growing SSBL	−0.499***	−1.215***	−0.849***	−0.990***	0.234	−0.365*	−0.152	−0.654***	−0.500***
	(0.0740)	(0.261)	(0.177)	(0.195)	(0.210)	(0.175)	(0.290)	(0.189)	(0.204)
Number of observations	10,774	1,373	1,378	1,457	1,452	872	1,208	1,448	1,586

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 3 of Table 5, with the exception of Japan where we have to control for decade dummies instead of five-year dummies in order to achieve convergence. Robust standard errors clustered by country, field of study and year of study.

field and 4: chose SSBL growing. To test whether men specifically avoid female-dominated growing fields, we run the following multinominal logit regression

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

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 6 displays the coefficients for male from this estimation. 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 larger. Men are hence less likely to choose growing fields, but this is specifically driven by them being less likely to choose growing female fields. In Table A-10 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).

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 Figs. A-3-A-9 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 A-7.

4.3. 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. Table 7 repeats results from our main wage regression and presents them separately for men and women. We only find a positive and significant wage effect of specializing in growing fields for women. For men the effect is not significantly different from zero. To check whether this result is driven by the genderedness of the fields, in columns 4–6 we include controls for gendered fields of study (female, male, SSBL) which we interact with an indicator for growth in related sectors (our omitted category is male fields that are not growing). While men earn higher wages (see columns 1 and 4) they experience significant wage penalties when specializing in traditionally female fields, even when those fields are growing (see columns 4 and 5). Gains from specializing in fields of study when related sectors are growing are gender-specific. They are only present for women who specialize in 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 A-11 in the Appendix shows the results. 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 degree. 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 vocational degrees for whom specializing in growing female fields or shrinking male fields is associated with equivalent wage outcomes. Hence, men's reluctance to obtain a vocational degree in growing female fields must be linked to non-monetary aspects, such as preferences, social stigma or discrimination.

5. Discussion and implications for the gender wage gap

To further investigate the importance of non-monetary aspects, we explore cross-country differences in our findings and relate them to data on gender norms from the World Value Survey. In Fig. A-10 in the Appendix we plot the absolute value of the negative coefficient for men's reluctance to go into growing fields against the share of individuals agreeing with the following two statements: "men have more right to a job than women when jobs are scarce" and "men make better political leaders than women do".[24] We also consider agreement with these state-

[24] Based on wave 5 of the World Value Survey, collected in 2005 for the UK, Japan, and Finland, in 2006 for the US, Sweden, Germany, and France, and in 2007 for Spain.

Table 7
Wage gains by gender and from choosing gendered fields.

	All	Men	Women	All	Men	Women
$growfield_{i,t-j}$	0.029	0.006	0.047	0.022	0.01	0.086
	(0.01)***	(0.014)	(0.014)***	(0.016)	(0.019)	(0.029)***
Male	0.148			0.132		
	(0.01)***			(0.01)***		
Chose Social Science Business Law (SSBL)				0.015	−.002	0.085
				(0.019)	(0.027)	(0.027)***
Chose female field of study				−.070	−.119	0.019
				(0.019)***	(0.028)***	(0.026)
Chose SSBL when growing				−.012	−.006	−.082
				(0.025)	(0.035)	(0.038)**
Chose female field when growing				0.033	0.049	−.044
				(0.025)	(0.038)	(0.036)
Country FE	x	x	x	x	x	x
Individual controls	x	x	x	x	x	x
Numeracy dummies	x	x	x	x	x	x
Non-cognitive controls	x	x	x	x	x	x
Year of specialization (5 year bins	x	x	x	x	x	x
Macroeconomic controls	x	x	x	x	x	x
Number of observations	8,018	3,603	4,415	8,018	3,603	4,415
Adjusted R-squared	0.284	0.291	0.243	0.286	0.296	0.245

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 3 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. Individual controls include dummy variables for vocational degree, foreign born, parents with secondary education, parents with tertiary education, years of job experience, and years of experience squared.

ments only among individuals with university degrees. In all four subfigures, we observe a positive cross-country relationship between the share of individuals agreeing with traditional gender norms and men's reluctance to specialize in growing fields.

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 Fig. A-11 in the Appendix we plot 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 Fig. 2 we graph the decrease in the gender wage gap for each country against the absolute value of the negative coefficient for men's reluctance to go into growing fields (from Table A-7; note that for Germany, France, and Spain, data on gender wage gaps is only available from 1992, 1995, and 2004 onward respectively). We observe a positive cross-country relationship, indicating that a greater aversion of men to specialize in growing fields is related to a larger reduction in gender wage gaps.

We also calculate the reduction in the gender wage gap that can be generated by gendered specialization decisions and our estimated returns to specializing in growing fields. 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. We then use our estimates from columns 5 and 6 of Table 7 to assign wage gains and losses to men and women based on their fields of specialization, and we predict the evolution of male and female wages (see Table A-12 in the Appendix for the share of men and women in different fields of specialization). Comparing our calculations to the actual change in the gender wage gap, we 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).[25] While these are rough calculations, together with Figs. 2 and A-11 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.[26]

[25] In the text that follows, we explain how we calculate the contribution of gendered specialization choices to changes in the gender wage gap. First using data from the OECD, we take the gender wage gap (median), and we normalize wages of men in 1980 to one. Wages for women in 1980 are set to 1- the gender wage gap. For instance, as the gender wage gap for Finland in 1980 was 26.62%, this means that wages of women in 1980 are set to 1-0.2662=0.7338. We then predict how wages of men and women would have evolved until 2012 only taking into account the share of men and women choosing growing and non-growing female, male, or neutral fields (Table A-12 in the Appendix), and we use the coefficients estimated in columns 5 and 6 of Table 7 that indicate the wage gains of having chosen each of these subcategories for men and women. For Finland, we predict men's wages in 2012 to be equal to 0.9775 and women's wages to be equal to 0.7617, and we estimate a hypothetical gender wage gap in 2012 of 1-(0.7617/0.9775) = 22%. Our predicted reduction in the gender wage gap for Finland is thus 4.6 percentage points. We then compare this to the reduction in the gender wage gap in the data which for Finland in 2012 is 7.9 percentage points (26.62- 18.73). Hence gendered specialization choices explain 58% of the reduction in the gender wage gap in Finland.

[26] Considering that the median gender wage gap might not be very representative for higher educated individuals, we follow Blau and Kahn (2017) and also consider gender wage gaps at higher deciles. Comparing our estimates to the change in the gender wage gap at the 9th decile we can explain 41% in Finland, 33% in the US, 36% in the UK, and 34% in Japan. For Sweden this data is not available.

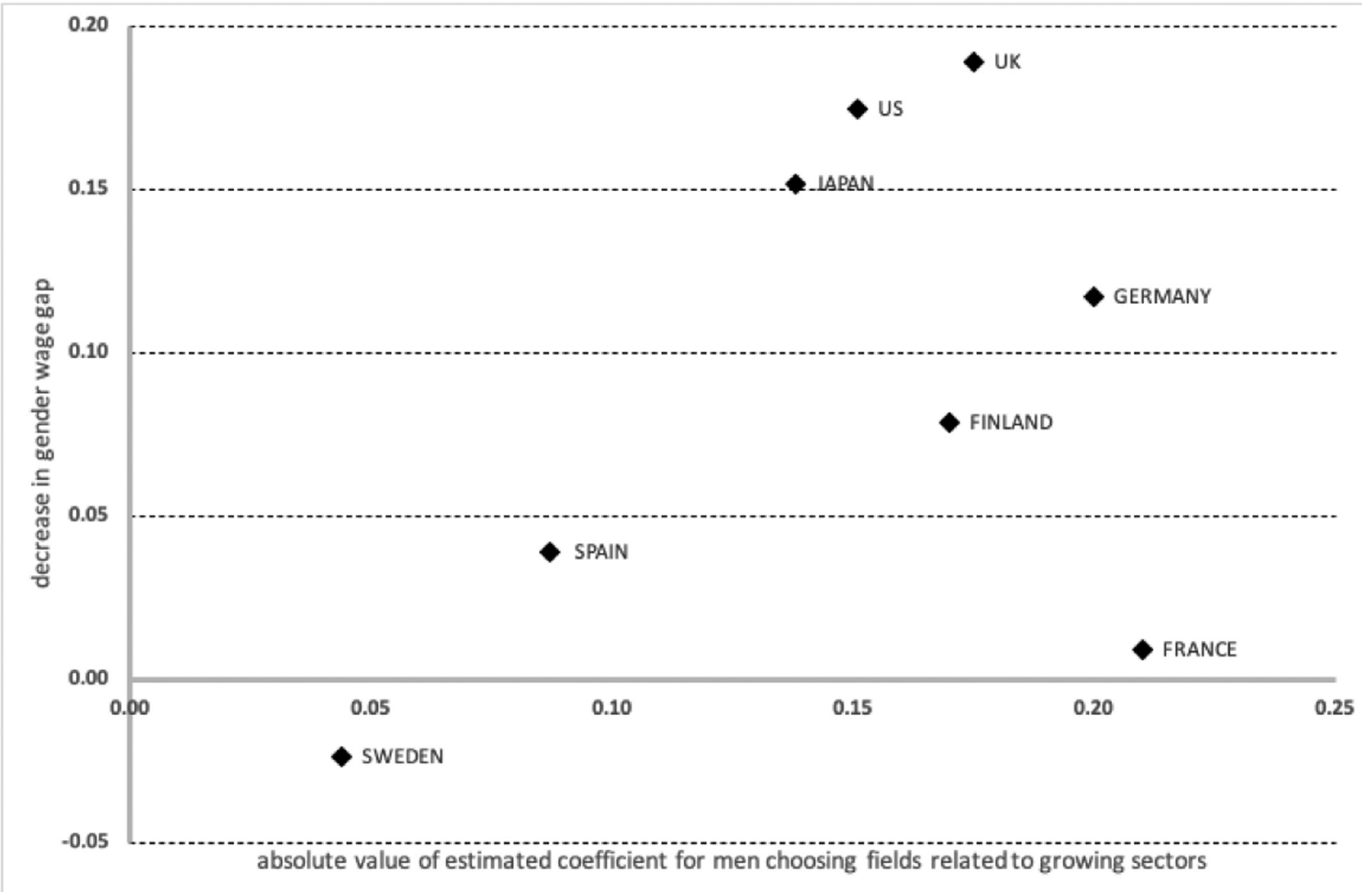

Fig. 2. Change in gender wage gap and estimated coefficients for men avoiding fields of study related to growing sectors.
OECD data on Gender Wage Gaps (median ratios of gross earnings); estimated coefficients from Table A-7.

6. 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, and 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. Testing for heterogeneity, we find men to be less likely to choose growing fields because they avoid traditionally female fields like health care and education whose related sectors 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 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.[27] When relating our findings to differences in gender norms across countries, we find support for this mechanism. Our results also 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.

Appendix A

A1. Figures

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

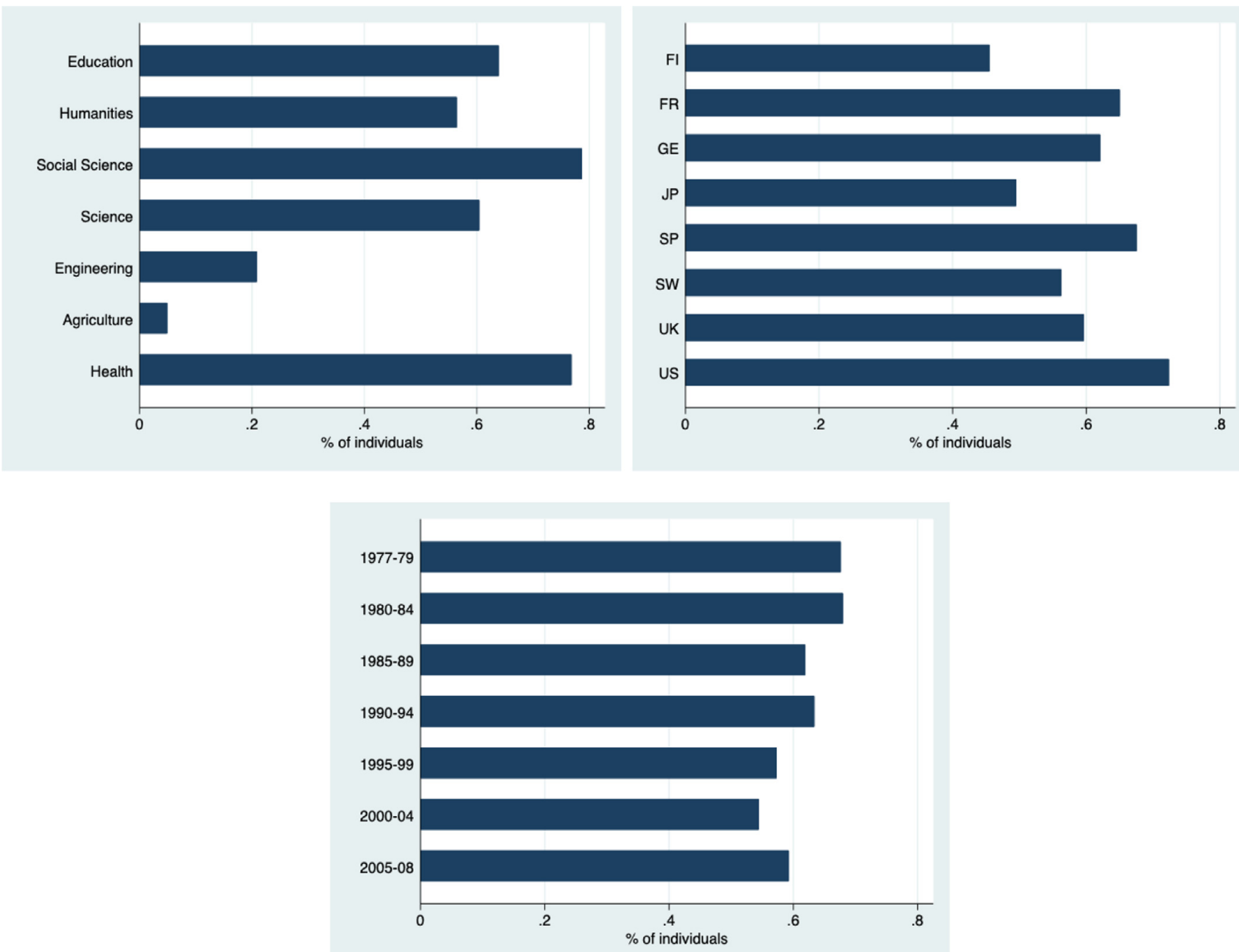

Fig. A-1. Fraction of individuals who specialized in a field of study when related sectors were growing by field, country, and year of specialization. PIAAC and national accounts data for each country; authors' own calculations.

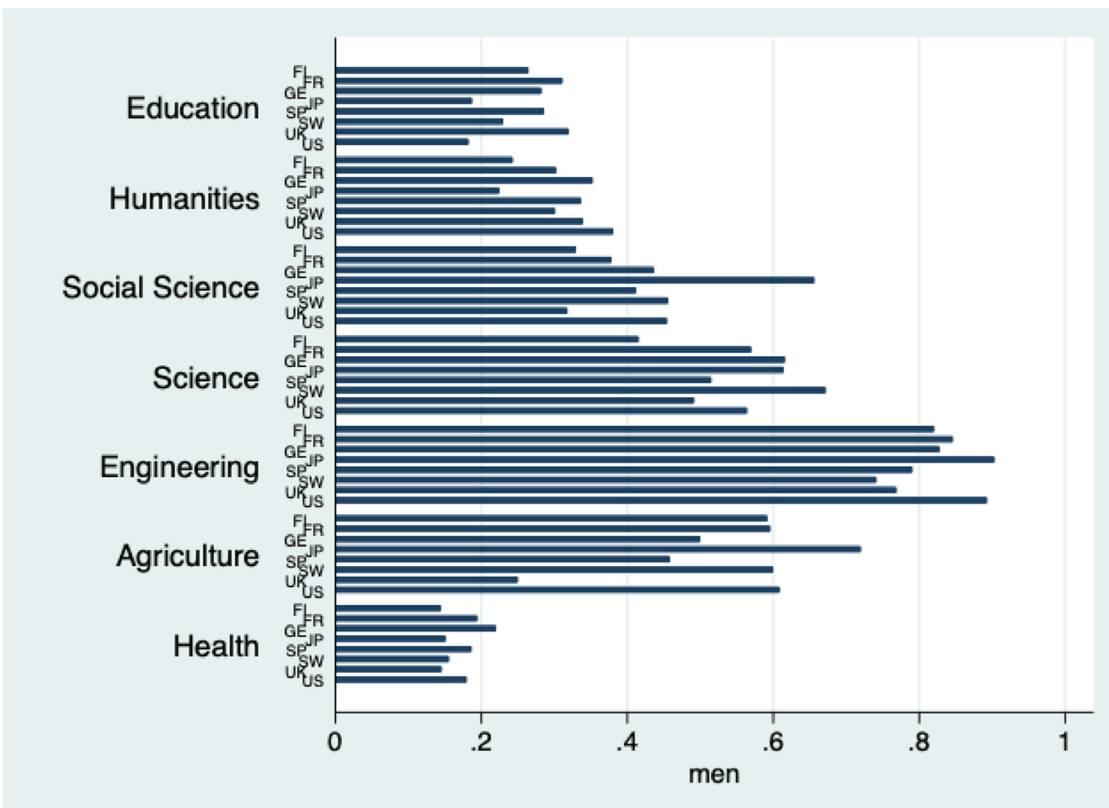

Fig. A-2. Share of men in different fields of study by country.
FI: Finland; FR: France: GE: Germany; JP: Japan; SP: Spain; SW: Sweden; PIAAC data; authors' own calculations.

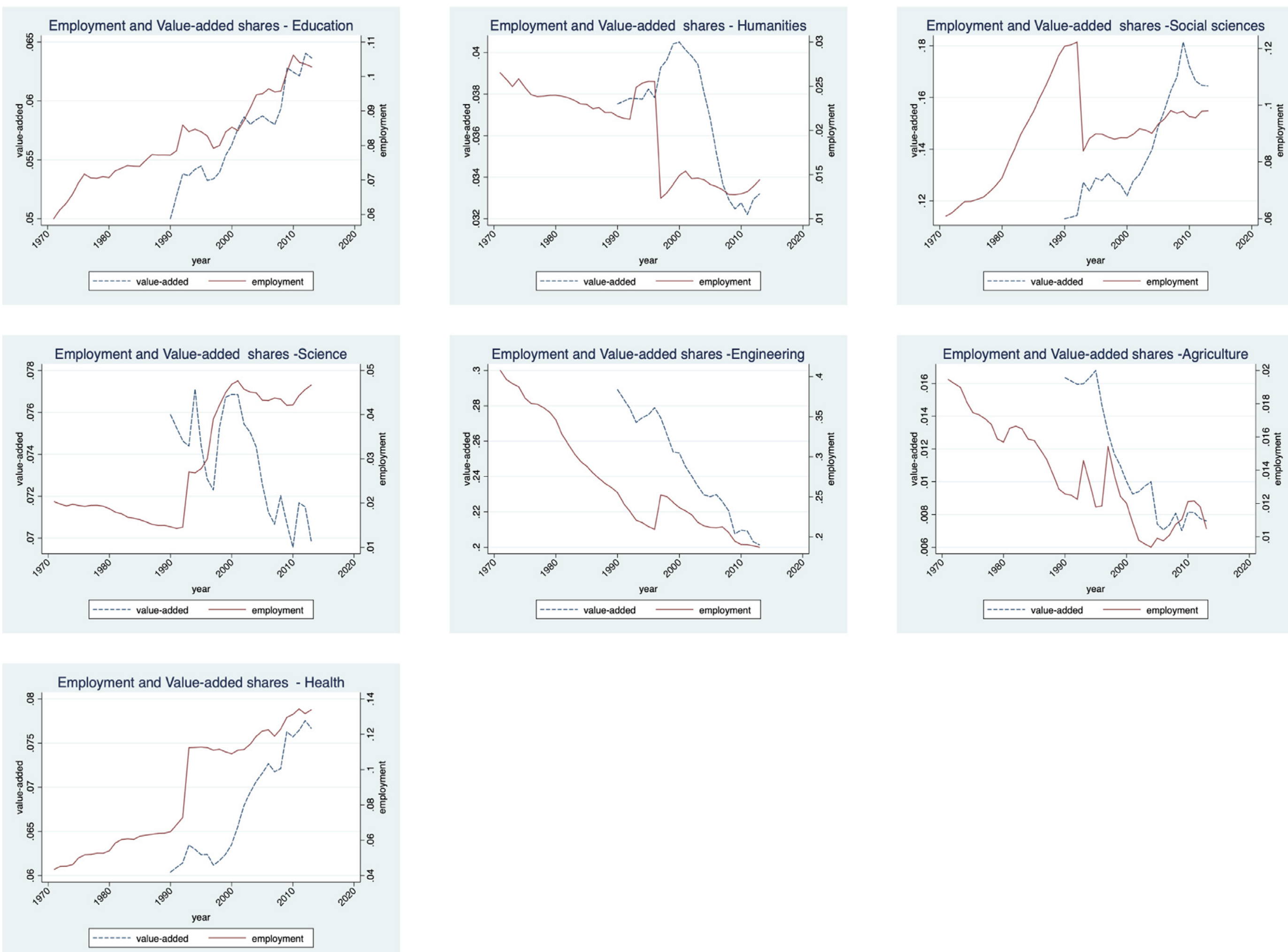

Fig. A-3. Value-added and employment shares, United Kingdom.
Data source: ONS; for details see the Companion Appendix.

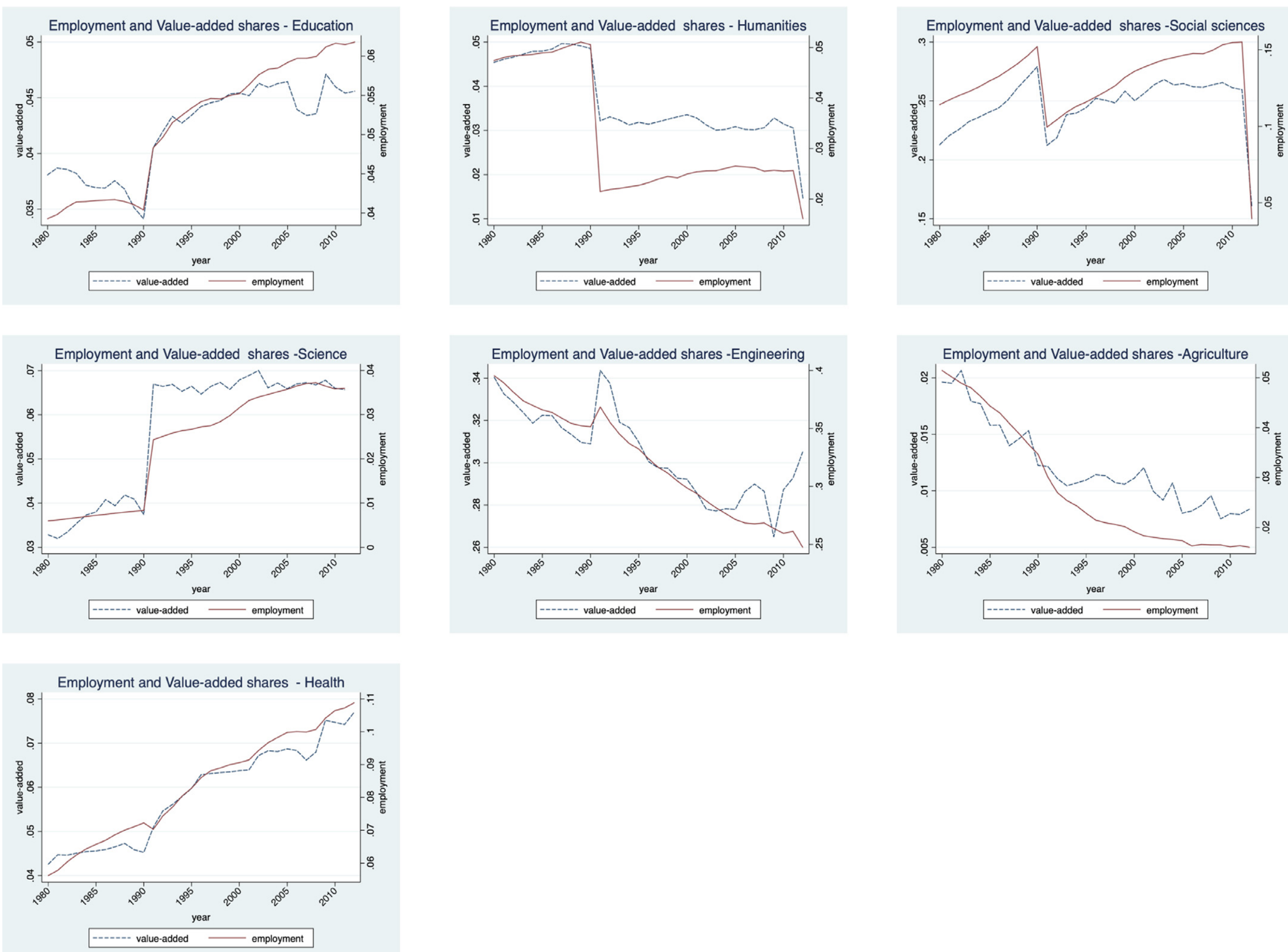

Fig. A-4. Value-added and employment shares, Germany.
Data source: Statistisches Bundesamt; for details see the Companion Appendix.

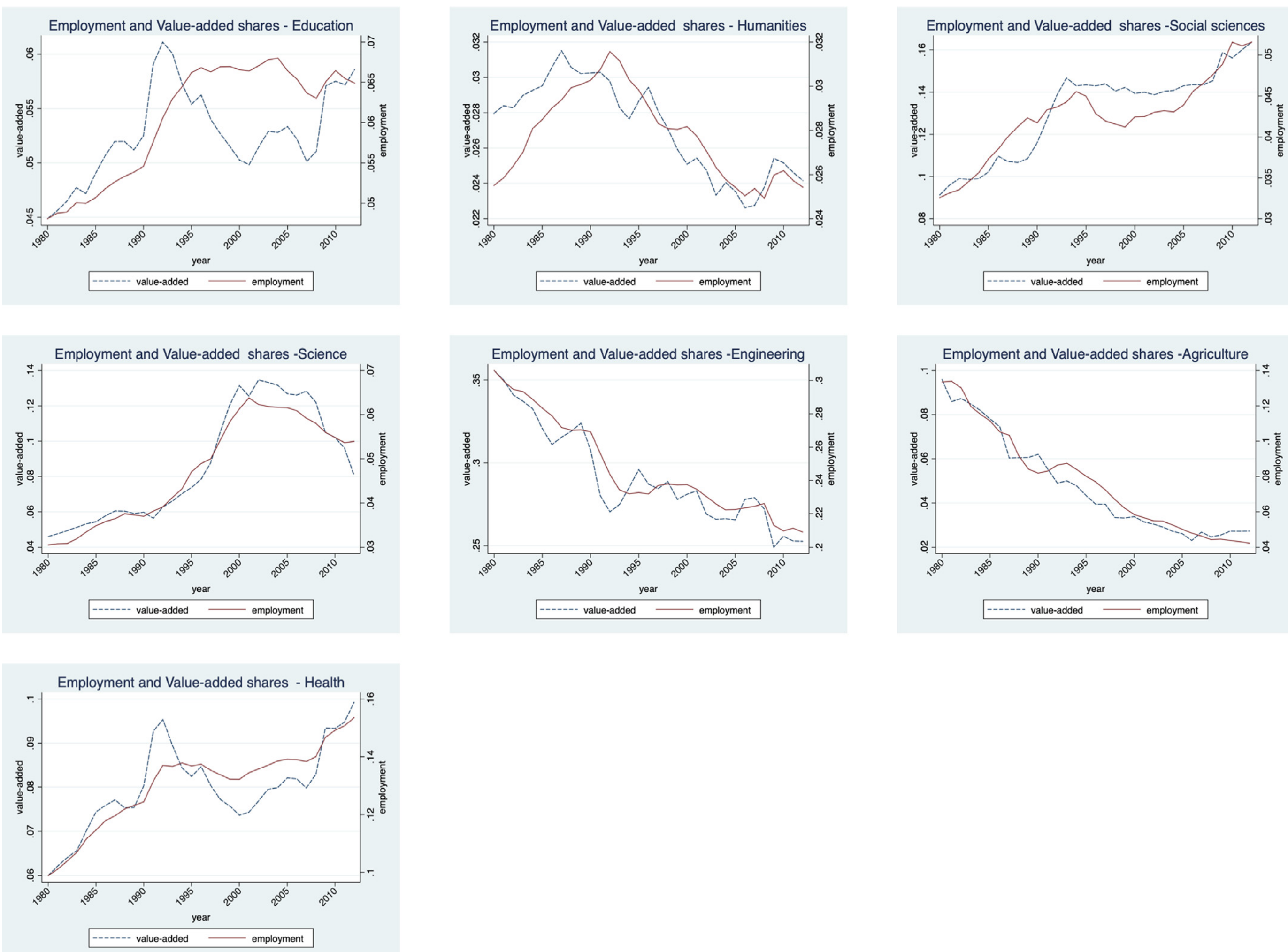

Fig. A-5. Value-added and employment shares, Finland.
Data source: OECD; authors' assignment to fields of study.

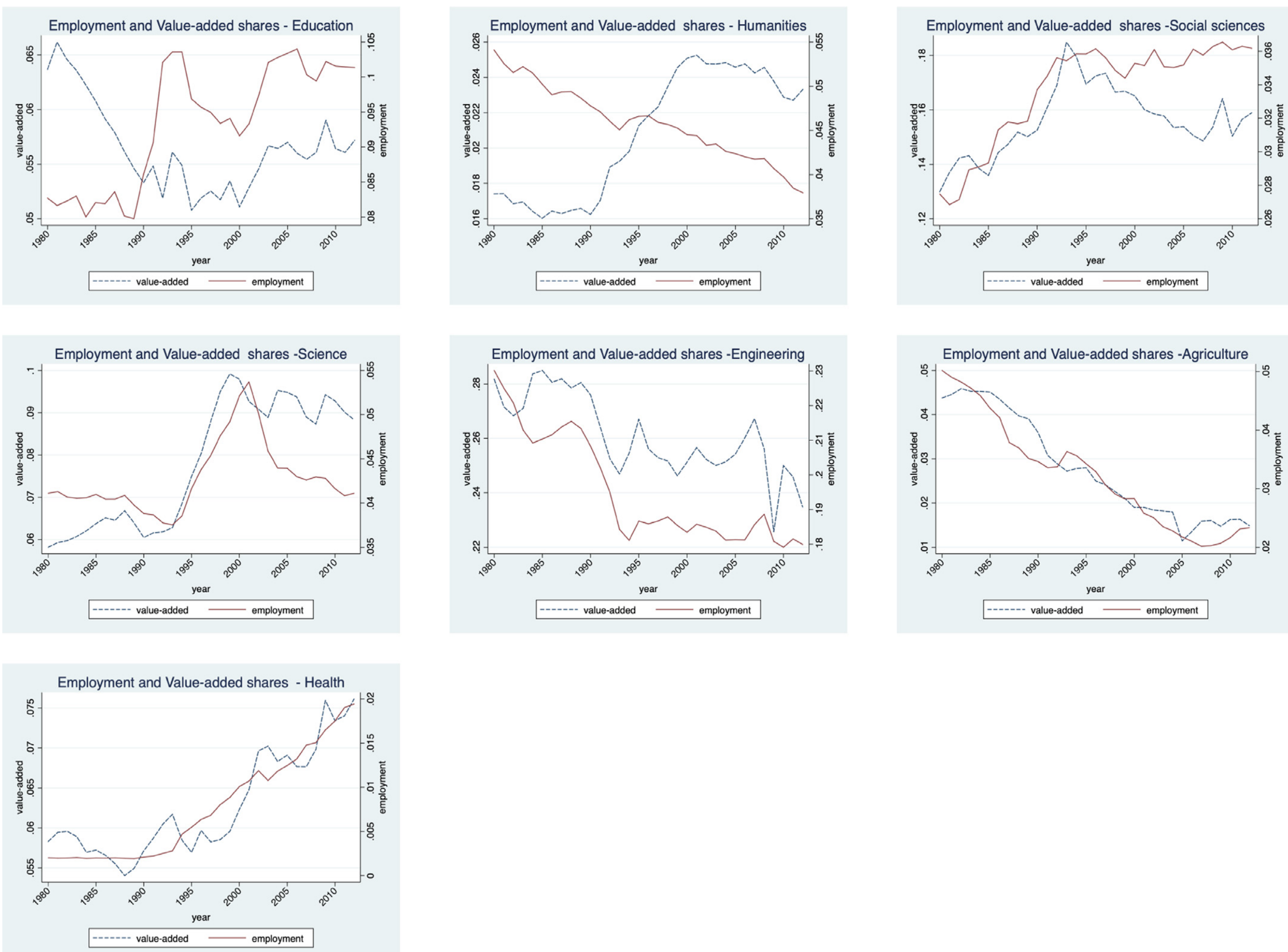

Fig. A-6. Value-added and employment shares, Sweden.
Data sources: Statistics Sweden and OECD; for details see the Companion Appendix.

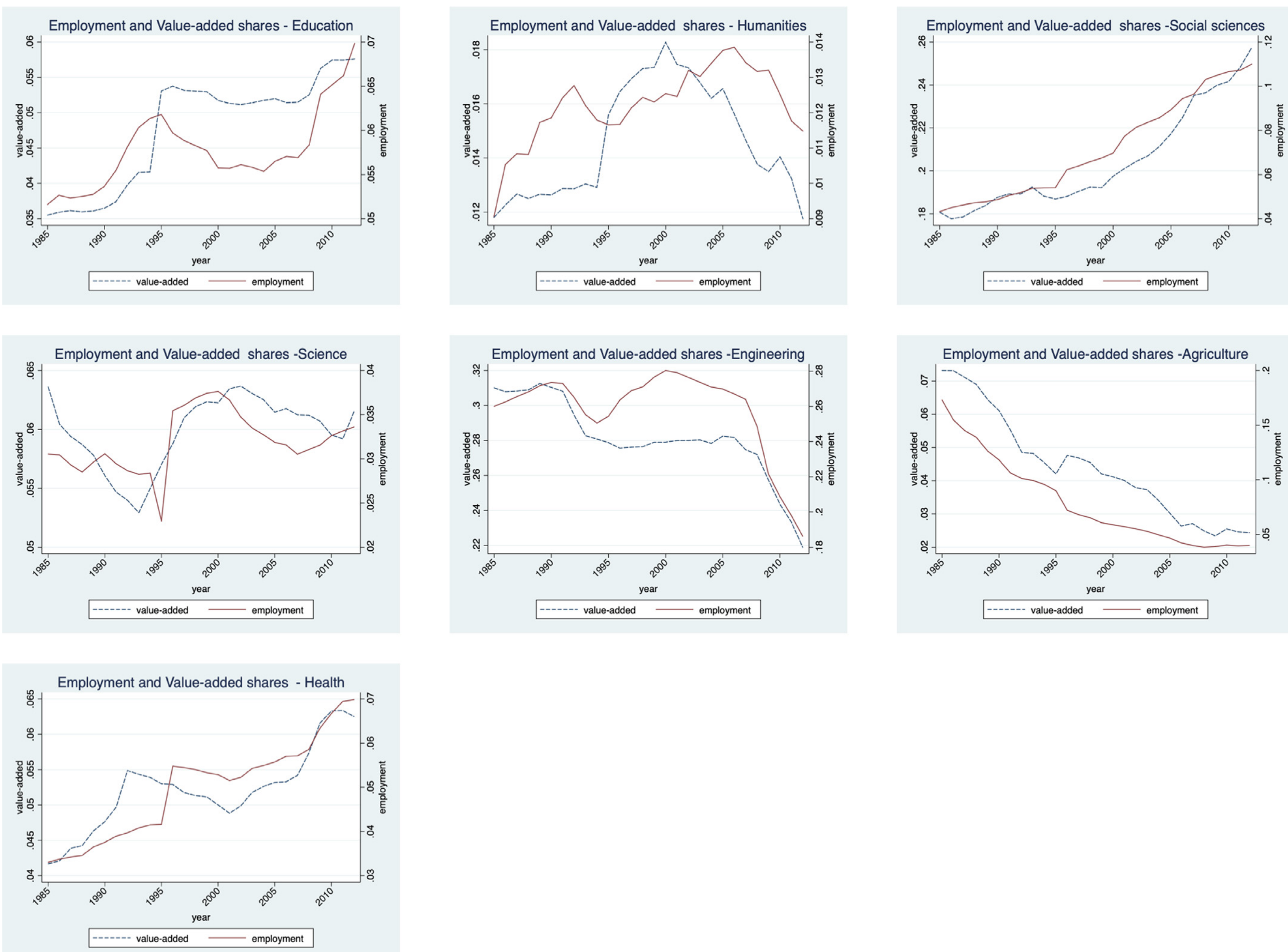

Fig. A-7. Value-added and employment shares, Spain.
Data source: INE; for details see the Companion Appendix.

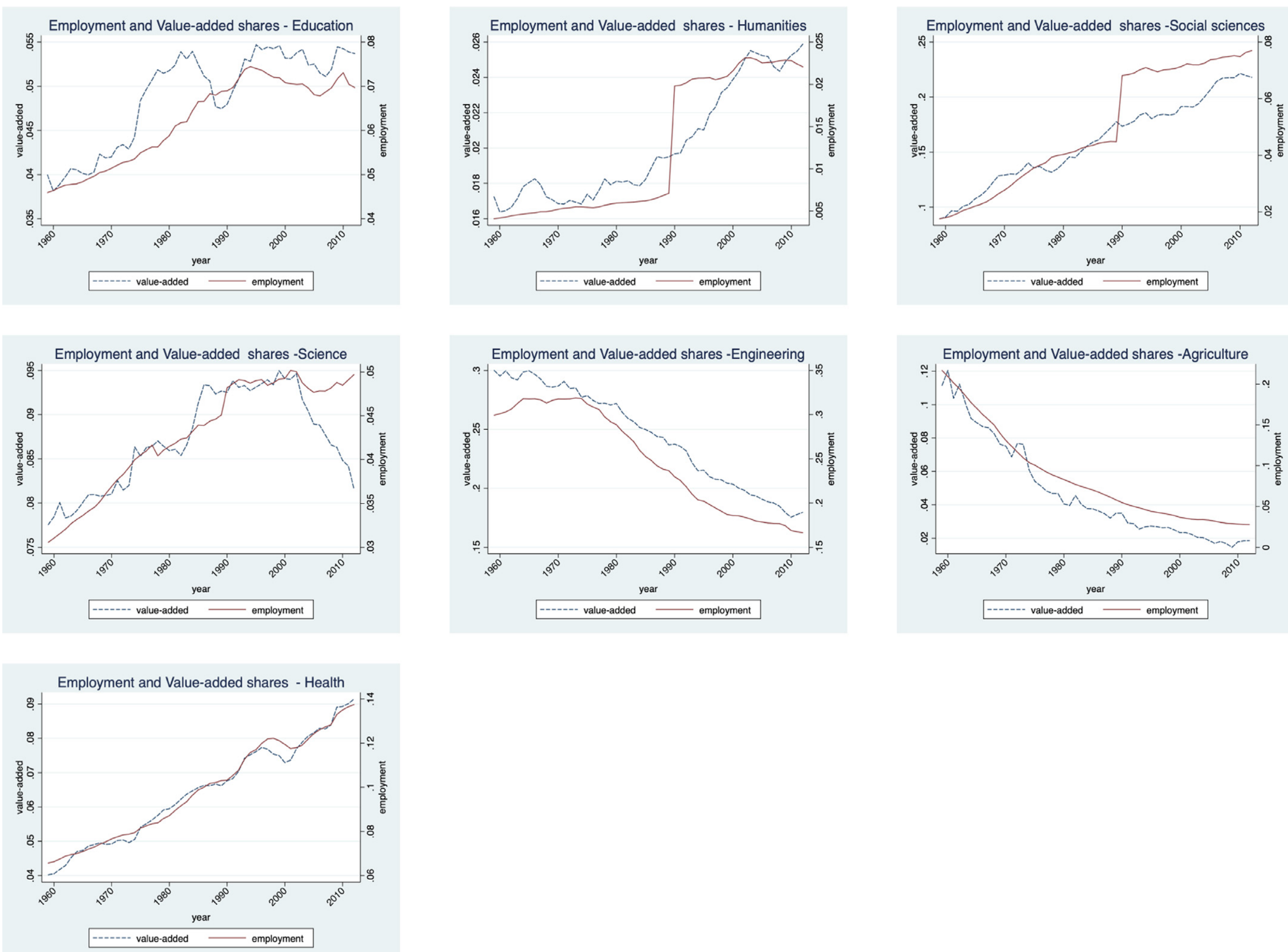

Fig. A-8. Value-added and employment shares, France.
Data sources: INSEE and OECD; for details see the Companion Appendix.

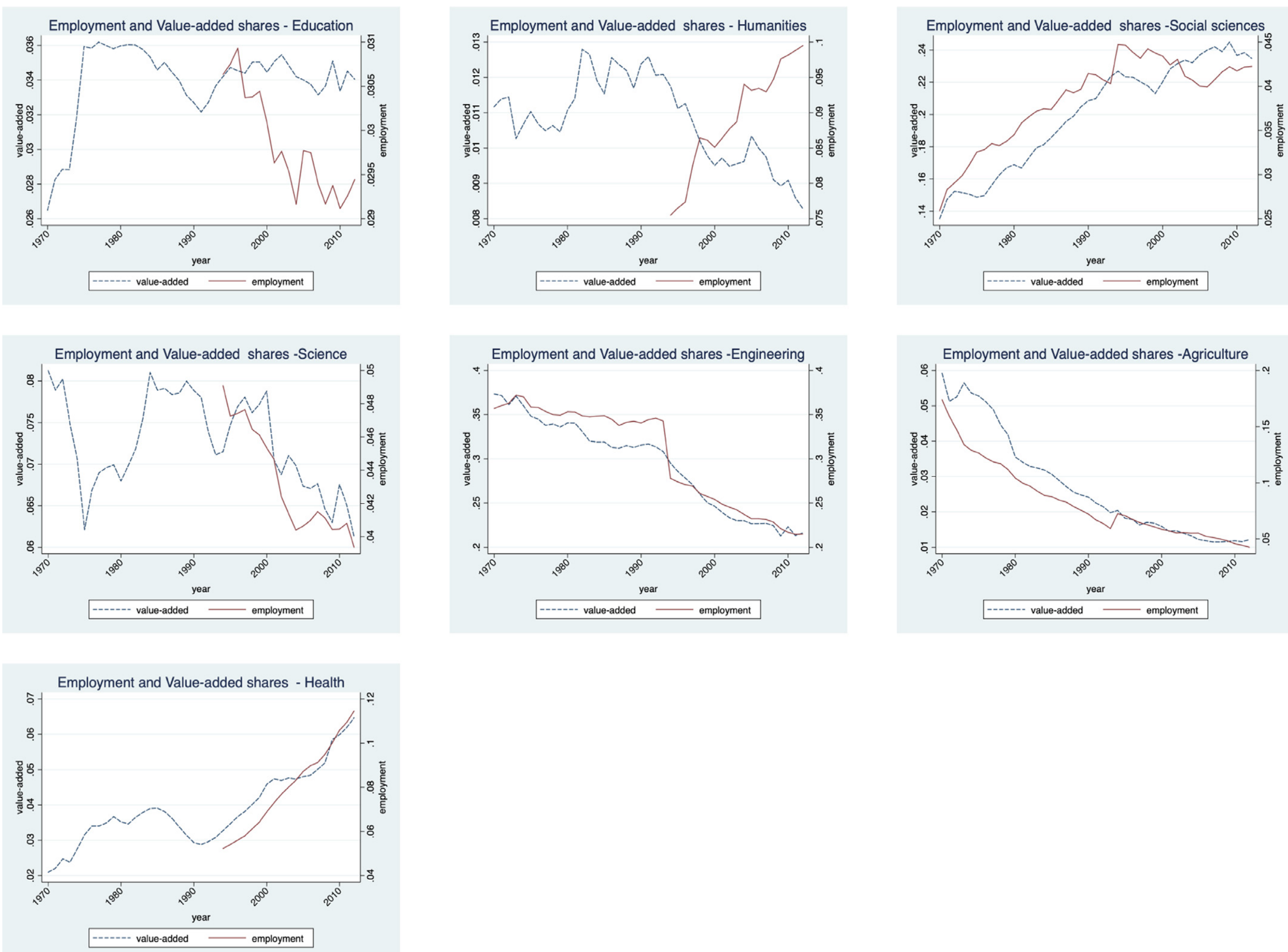

Fig. A-9. Value-added and employment shares, Japan.
Data sources: Statistics Japan and OECD; for details see the Companion Appendix.

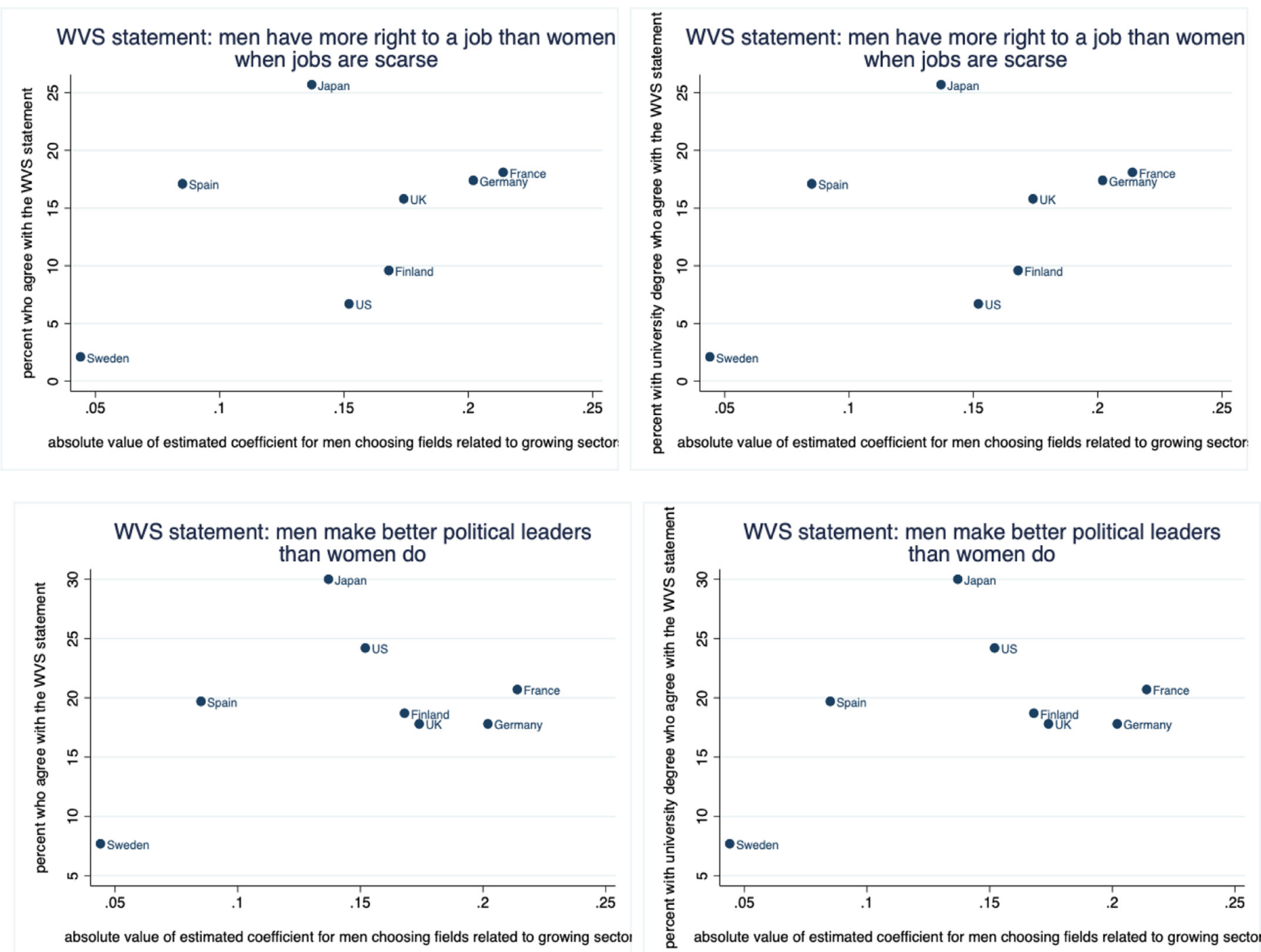

Fig. A-10. Share of individuals agreeing with traditional gender norms and estimated coefficients on men's reluctance to choose growing fields.
Wave 5 of the World Value Survey; authors' own calculations, see Table A-7.

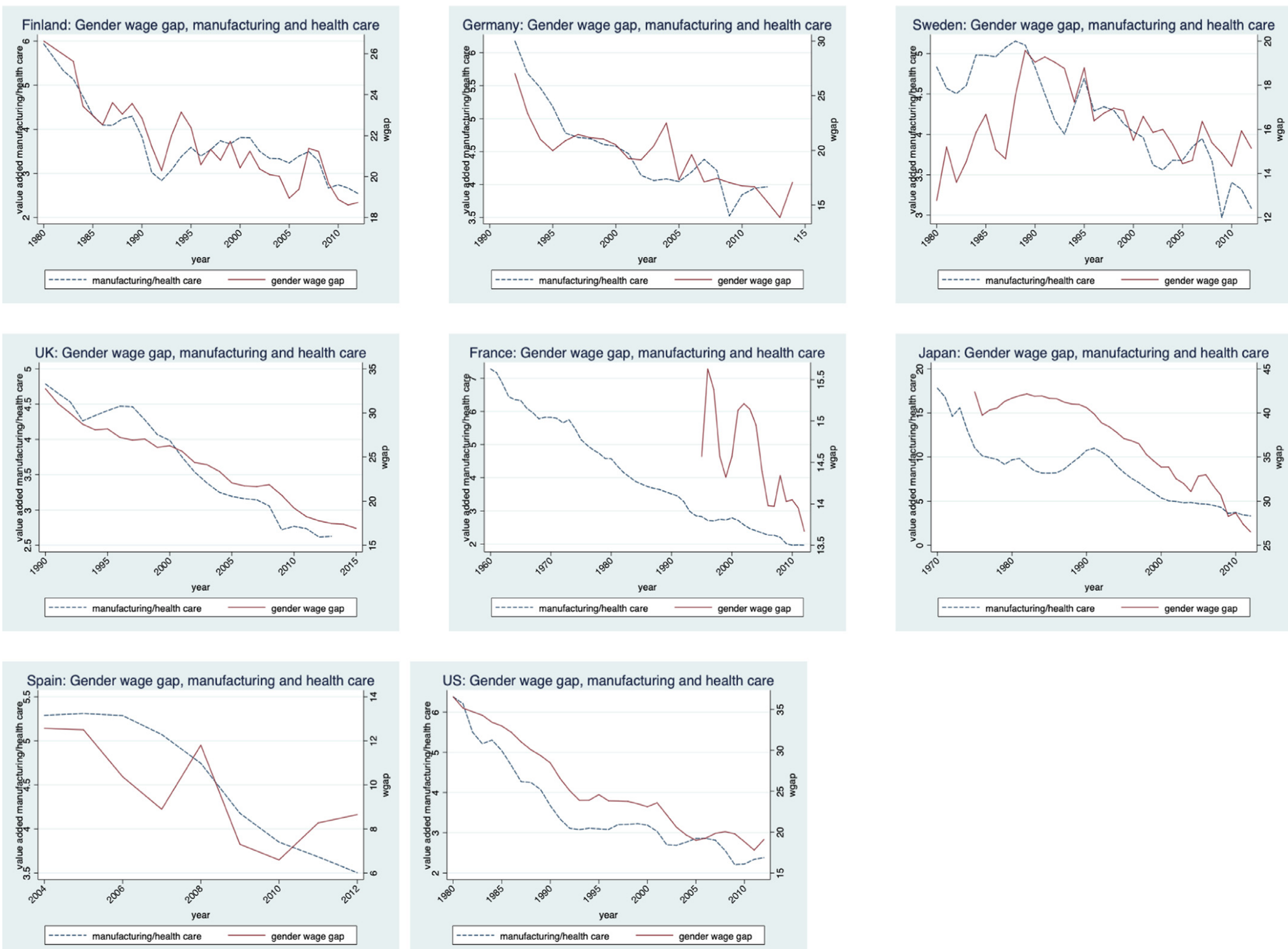

Fig. A-11. Gender wage gaps and ratio of value added in manufacturing to health care.
Source: OECD for gender wage gaps.

A2. Tables

Table A-1
Data sources.

Variable	Source
Value added shares by sectors	
United States	BEA
United Kingdom	ONS
France	INSEE
Germany	Statistisches Bundeamt
Japan	Statistics Japan
Spain	INE
Sweden	Cabinet Office Statistics Sweden
Additional macroeconomic variables	
% contracts covered by collective bargaining	Visser (2013)
Public expenditure to GDP	
Germany	Statistisches Bundesamt
United Kingdom	ONS
United States	BEA
all other countries	World Bank Data
Quarterly real GDP per capita	
Finland	Statistics Finland and OECD
France	INSEE
Germany	Statistisches Bundesamt
Japan	Statistics Japan
Spain	INE
United Kingdom	ONS
United States	St. Louis Federal Reserve
Employment by sectors	
Finland	OECD
France	OECD
Germany	Statistisches Bundesamt
Japan	Statistics Japan and OECD
Spain	INE
Sweden	Statistics Sweden and OECD
United Kingdom	ONS
United States	Bureau of Labor Statistics; US Agriculture Ministry

Table A-2
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	0.328
	(0.021)***	(0.009)***
Constant	0.292	0.381
	(0.016)***	(0.007)***
Number of observations	1,786	10,774
R-squared	0.19	0.106
B. Sectors related to field of study grow in $t+1$		
$growfield_{t-4}$	0.350	0.221
	(0.023)***	(0.010)***
Constant	0.336	0.443
	(0.017)***	(0.008)***
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	0.181
	(0.023)***	(0.010)***
Constant	0.352	0.454
	(0.017)***	(0.008)***
Number of observation	1,674	10,154
R-squared	0.097	0.032

Results from the following regression: $growfield_{t+k} = \beta_0 + \beta_1 growfield_{t-4} + \epsilon$. 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.

Table A-3
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
Adjusted R-squared	0.305	0.097	0.211	0.119	0.112	0.259	0.025

Results from the following regression: $spec_{f,i} = \beta_1 grow_{f,t-2} + \beta_2 grow_{f,t-3} + \beta_3 grow_{f,t-4} + \beta_4 F_i + \beta_5 VD_i + \epsilon_{i,f}$, where $spec_{f,i}$ indicates whether individual i specialized in field f (f = Engineering, Health Care, Education, ...etc) $grow_{f,t-2}$, $grow_{f,t-3}$, 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. 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. Fewer observations for science because assignment of sectors to field of study in US only from 1977 onwards.

Table A-4
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)
$growfield_{i,age18}$	0.014	0.03	0.029	0.031	0.026	0.001
	(0.014)	(0.011)***	(0.01)***	(0.011)***	(0.011)**	(0.013)
Male		0.152	0.146	0.126	0.124	0.117
		(0.011)***	(0.01)***	(0.011)***	(0.011)***	(0.011)***
Vocational degree		−.205	−.190	−.217	−.217	−.212
		(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***
Job experience		0.037	0.02	0.021	0.022	0.022
		(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Experience squared/100		−.070	−.043	−.047	−.046	−.047
		(0.008)***	(0.01)***	(0.01)***	(0.009)***	(0.009)***
Foreign born		−.052	−.058	−.058	−.062	−.059
		(0.02)**	(0.02)***	(0.02)***	(0.02)***	(0.02)***
Parental education: secondary		0.027	0.037	0.036	0.035	0.032
		(0.014)**	(0.014)***	(0.013)***	(0.013)**	(0.013)**
Parental education: tertiary		0.056	0.07	0.073	0.074	0.072
		(0.013)***	(0.013)***	(0.013)***	(0.013)***	(0.013)***
Numeracy: Level 2		0.093	0.097	0.103	0.102	0.097
		(0.029)***	(0.029)***	(0.029)***	(0.029)***	(0.029)***
Numeracy: Level 3		0.167	0.17	0.177	0.174	0.169
		(0.028)***	(0.028)***	(0.028)***	(0.028)***	(0.028)***
Numeracy: Level 4 or 5		0.252	0.257	0.254	0.246	0.239
		(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***
Works in related occupation						0.059
						(0.018)***
$growfield_{i,age18}$×works related						0.091
						(0.022)***
Country FE	x	x	x	x	x	x
Non-cognitive ability		x	x	x	x	x
Macroeconomic controls				x	x	x
Year age 18 (5 year bins)				x	x	x
Field dummies					x	x
Field-Country dummies						x
Number of observations	6,938	6,938	6,938	6,938	6,938	6,938
Adjusted R-squared	0.1	0.286	0.306	0.323	0.332	0.341

The dependent variable are log hourly wages in 2011/12. $growfield_{i,age18}$ 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 A-5
Specialization in fields of study when related sectors are growing and hourly wages later in life - Heckman selection models.

	Full sample		Full sample		Women		Women	
	log hourly wage	worked last week	log hourly wage	worked last week	log hourly wage	worked last week	log hourly wage	worked ast week
$growfield_{i,t-j}$	0.026***	−0.006	0.018*	−0.026	0.046***	0.001	0.025*	−0.030
	(0.010)	(0.032)	(0.010)	(0.034)	(0.013)	(0.041)	(0.014)	(0.043)
Job experience	0.049***	0.061***	0.050***	0.066***	0.047***	0.075***	0.048***	0.081***
	(0.007)	(0.023)	(0.007)	(0.023)	(0.009)	(0.028)	(0.009)	(0.028)
Experience squared/100	−0.105***	−0.201***	−0.108***	−0.214***	−0.095***	−0.217**	−0.099***	−0.236***
	(0.022)	(0.070)	(0.022)	(0.071)	(0.030)	(0.088)	(0.029)	(0.089)
Vocational degree	−0.208***	−0.154***	−0.236***	−0.198***	−0.180***	−0.094**	−0.206***	−0.143***
	(0.012)	(0.036)	(0.012)	(0.037)	(0.015)	(0.045)	(0.016)	(0.046)
Male	0.160***	0.417***	0.147***	0.412***				
	(0.015)	(0.032)	(0.015)	(0.035)				
Foreign born	−0.051***	−0.280***	−0.050***	−0.276***	−0.075***	−0.325***	−0.064***	−0.316***
	(0.019)	(0.049)	(0.019)	(0.050)	(0.024)	(0.061)	(0.024)	(0.062)
Parental education: secondary	0.008	−0.088**	0.008	−0.088**	0.010	−0.125**	0.012	−0.125**
	(0.013)	(0.042)	(0.013)	(0.042)	(0.017)	(0.052)	(0.017)	(0.052)
Parental education: tertiary	0.029**	−0.155***	0.034**	−0.149***	0.048***	−0.200***	0.056***	−0.194***
	(0.013)	(0.043)	(0.013)	(0.043)	(0.018)	(0.054)	(0.018)	(0.055)
Health: poor or fair		−0.462***		−0.460***		−0.412***		−0.408***
		(0.046)		(0.046)		(0.058)		(0.058)
background - children		−0.171***		−0.188***		−0.441***		−0.456***
		(0.035)		(0.035)		(0.044)		(0.045)
Constant	2.801***	0.176	2.837***	0.240	2.674***	0.105	2.750***	0.152
	(0.098)	(0.281)	(0.096)	(0.283)	(0.127)	(0.359)	(0.125)	(0.362)
Country FE	x	x	x	x	x	x	x	x
Numeracy levels	x	x	x	x	x	x	x	x
Non-cognitive ability	x	x	x	x	x	x	x	x
Macroeconomic controls	x	x	x	x	x	x	x	x
Year of specialization (5 year bins)	x	x	x	x	x	x	x	x
Field dummies			x	x			x	x
Observations	9,515	9,515	9,515	9,515	5,457	5,457	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 columns 3 and 4 of Table 4.

Table A-6
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)
$growth/VA_{i,t-j}$	0.113	0.164	0.177	0.101	0.072	−.087
	(0.063)*	(0.047)***	(0.047)***	(0.051)**	(0.051)	(0.058)
Male		0.147	0.148	0.135	0.133	0.129
		(0.01)***	(0.01)***	(0.011)***	(0.01)***	(0.01)***
Vocational degree		−.200	−.201	−.229	−.229	−.223
		(0.011)***	(0.011)***	(0.012)***	(0.012)***	(0.012)***
Job experience		0.036	0.048	0.05	0.051	0.051
		(0.002)***	(0.008)***	(0.007)***	(0.006)***	(0.006)***
Experience squared/100		−.068	−.102	−.106	−.109	−.110
		(0.008)***	(0.025)***	(0.023)***	(0.021)***	(0.021)***
Foreign born		−.052	−.053	−.054	−.058	−.053
		(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***
Parental education: secondary		0.013	0.015	0.014	0.013	0.012
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Parental education: tertiary		0.036	0.037	0.041	0.042	0.042
		(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.011)***
Numeracy: Level 2		0.106	0.105	0.108	0.108	0.101
		(0.025)***	(0.025)***	(0.025)***	(0.025)***	(0.025)***
Numeracy: Level 3		0.178	0.177	0.183	0.18	0.173
		(0.024)***	(0.024)***	(0.024)***	(0.024)***	(0.024)***
Numeracy: Level 4 or 5		0.259	0.257	0.254	0.246	0.238
		(0.027)***	(0.027)***	(0.027)***	(0.027)***	(0.027)***
Works in related occupation						0.099
						(0.012)***
$growth/VA_{i,t-j}$×works related						0.569
						(0.094)***
Country FE	x	x	x	x	x	x
Non-cognitive ability		x	x	x	x	x
Macroeconomic controls			x	x	x	x
Year of specialization (5 year bins)			x	x	x	x
Field dummies				x	x	x
Field-Country dummies					x	x
Number of observations.	8,018	8,018	8,018	8,018	8,018	8,018
Adjusted R-squared	0.101	0.283	0.284	0.302	0.313	0.323

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 A-7
Individual characteristics related to specializing in growing fields of study - by country.

	fin	fra	ger	jpn	esp	swe	uk	us
Male	−.166	−.213	−.202	−.138	−.085	−.041	−.175	−.150
	(0.052)***	(0.037)***	(0.044)***	(0.049)***	(0.041)**	(0.041)	(0.044)***	(0.037)***
Vocational degree	−.002	−.076	0.016	−.005	−.122	−.056	−.071	−.109
	(0.028)	(0.035)**	(0.047)	(0.04)	(0.042)***	(0.035)	(0.037)*	(0.049)**
Foreign born	0.017	−.058	−.069	−.025	0.018	0.002	−.085	−.140
	(0.072)	(0.038)	(0.042)*	(0.271)	(0.056)	(0.044)	(0.035)**	(0.037)***
Numeracy: Level 4 or 5	−.145	−.231	0.074	−.100	−.045	−.109	−.069	−.022
	(0.079)*	(0.053)***	(0.073)	(0.101)	(0.082)	(0.08)	(0.052)	(0.049)
Number of observations	1,373	1,378	1,457	1,452	872	1,208	1,448	1,586
Adjusted R-squared	0.197	0.09	0.07	0.071	0.065	0.016	0.048	0.064

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 3 of Table 5). Heteroskedasticity robust standard errors clustered by country, field of study and year.

Table A-8
Robustness Check: Determinants of specializing in fields of study - controlling for graduates after last economic crisis.

	(1)	(2)
Male	−.154	−.155
	(0.016)***	(0.016)***
Specialized after 2008	0.001	−.038
	(0.129)	(0.13)
Male x specialized aft. 2008		0.08
		(0.099)
Vocational degree	−.041	−.042
	(0.016)***	(0.016)***
Foreign born	−.054	−.054
	(0.017)***	(0.017)***
Numeracy Level: 4 or 5	−.076	−.077
	(0.023)***	(0.023)***
Number of observations.	10,774	10,774
Adjusted R-squared	0.069	0.069

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 3 of Table 5). Heteroskedasticity robust standard errors clustered by country, field of study and year of study.

Table A-9
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	−.118
	(0.014)***	(0.015)***
Vocational degree	−.130	−.073
	(0.019)***	(0.017)***
Number of observations	10,774	10,774
Adjusted R-squared	0.074	0.063

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 3 of Table 5. Heteroskedasticity robust standard errors clustered by country, field of study and year of study.

Table A-10
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	−1.053***	−2.037***
	(0.0796)	(0.132)
Growing male field	0.378***	0.305*
	(0.115)	(0.175)
Growing SSBL	−0.285***	−1.065***
	(0.0778)	(0.138)
Number of observations	7,199	3,575

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 3 of Table 5. Robust standard errors clustered by country, field of study and year of study.

Table A-11
Gendered wage gains from choosing growing female fields of study - by degree type.

	All	Vocational	University
Men in growing female fields	−.068	−.042	−.086
	(0.021)***	(0.039)	(0.025)***
Men in growing male fields	0.004	0.024	−.014
	(0.02)	(0.032)	(0.025)
Men in shrinking female fields	−.125	−.164	−.137
	(0.027)***	(0.062)***	(0.031)***
Women in growing female fields	−.158	−.121	−.185
	(0.015)***	(0.023)***	(0.019)***
Women in growing male fields	−.134	−.094	−.162
	(0.024)***	(0.042)**	(0.03)***
Women in shrinking female fields	−.210	−.170	−.234
	(0.018)***	(0.031)***	(0.023)***
Women in shrinking male field	−.218	−.244	−.216
	(0.022)***	(0.04)***	(0.027)***
Men in SSBL	−.003	0.001	−.021
	(0.016)	(0.029)	(0.02)
Women in SSBL	−.127	−.122	−.137
	(0.015)***	(0.024)***	(0.02)***
Individual controls	x	x	x
Numeracy dummies	x	x	x
Non-cognitive controls	x	x	x
Year of graduation (5 year bins	x	x	x
Macroeconomic controls	x	x	x
Number of observations	8,018	2,555	5,463
Adjusted R-squared	0.288	0.28	0.26

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 3 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. Individual controls include dummy variables for vocational degree, foreign born, parents with secondary education, parents with tertiary education, years of job experience, and years of experience squared.

Table A-12
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

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2021.101994.

References

Aina, C., Baici, E., Casalone, G., 2011. Time to degree: students' abilities, university characteristics or something else? Evidence from Italy. Educ. Econ. 19 (3), 311–325.
Akerlof, G.A., Kranton, R.E., 2000. Economics and identity. Q. J. Econ. 115 (3), 715–753.
Almlund, M., Duckworth, A.L., Heckman, J.J., Kautz, T.D., 2011. Personality psychology and economics. In: Hanushek, E., Machin, S., Woessman, L. (Eds.), Handbook of the Economics of Education,. Elsevier, Amsterdam.
Altonji, J.G., Blom, E., Meghir, C., 2012. Heterogeneity in human capital investments: high school curriculum, college major, and careers. Annu. Rev. Econ. 4, 185–223.
Altonji, J.G., Kahn, L.B., Speer, J.D., 2016. Cashier or consultant? Entry labor market conditions, field of study, and career success. J. Labor Econ. 34 (S1), 361–401.
Aparicio Fenoll, A., 2016. Returns to education and educational outcomes: the case of the spanish housing boom. J. Hum. Cap. 10 (2), 235–265.
Arcidiacono, P., 2004. Ability sorting and the returns to college major. J. Econom. 121 (1–2), 343–375.
Arcidiacono, P., Hotz, J.V., Kang, S., 2012. Modeling college major choices using elicited measures of expectations and counterfactuals. J. Econom. 166 (1), 3–16.
Autor, D.H., Dorn, D., Hanson, G., 2019. When work disappears: Manufacturing decline and the falling marriage value of young men. Am. Econ. Rev. 1 (2), 161–178.
Beffy, M., Fougre, D., Maurel, A., 2012. Choosing the field of study in postsecondary education: do expected earnings matter? Rev. Econ. Stat. 94 (1), 334–347.
Berger, M., 1988. Predicted future earnings and choice of college major. Ind. Labor Relat. Rev. 41 (3), 418–429.
Black, D.A., Haviland, A., Sanders, S.G., Taylor, L.J., 2008. Gender wage disparities among the highly educated. J. Hum. Resour. 43 (3), 630–659.
Blau, F.D., Kahn, L.M., 2017. The gender wage gaps: extent, trends and explanations. J. Econ. Lit. 55 (3), 789–865.
Blom, E., Cadena, B.C., Keys, B.J., 2015. Investment over the Business Cycle: Insights from College Major Choice. Discussion Paper No. 9167. IZA.
Chira, S., 2017. Men Don't Want to be Nurses. Their Wives Agree. New York Times.
Choi, D., Lou, D., Mukherjee, A., 2016. The effect of superstar firms on college major choice. unpublished manuscript.
Cortes, G.M., Jaimovich, N., Siu, H.E., 2018. The "End of Men" and Rise of Women in the High-Skilled Labor Market. Working Paper 24274. NBER.
Gemici, A., Wiswall, M., 2014. Evolution of gender differences in post-secondary human capital investments: college majors. Int. Econ. Rev. 55 (1), 23–56.
Goldin, C.A., 2014. A grand gender convergence: its last chapter. Am. Econ. Rev. 104 (4), 1091–1119.
Hanushek, E.A., Schwerd, G., Wiederhold, S., Woessmann, L., 2015. Returns to skills around the world: evidence from PIAAC. Eur. Econ. Rev. 73, 103–130.
Kahn, L.B., 2010. The long-term labor market consequences of graduating from college in a bad economy. Labour Econ. 45 (3), 303–316. 17(2)
Long, M.C., Goldhaber, D., Huntington-Klein, N., 2015. Do completed college majors respond to changes in wages? Econ. Educ. Rev. 49, 1–14.
Machin, S., Puhani, P.A., 2003. Subject of degree and the gender wage differential: evidence from the UK and Germany. Econ. Lett. 79 (3), 393–400.
Messer, D., Wolter, S., 2010. Time-to-degree and the business cycle. Educ. Econ. 18 (1), 111–123.
Montmarquette, C., Cannings, K., Mahseredjian, S., 2002. How do young people choose college majors? Econ. Educ. Rev. 21 (6), 543–556.
Neal, D., 1995. Industry-specific human capital: evidence from displaced workers. J. Labor Econ. 13 (4), 653–677.
Ngai, L.R., Petrongolo, B., 2017. Gender gaps and the size of the service sector. Am. Econ. J. 9 (4), 1–44.
OECD, 2013. Closing the Gender Gap: Act Now. Organization for Economic Co-operation and Development, Paris.
Oreopoulos, P., von Wachter, Heisz, T., Andrew, 2012. The short- and long- term career effects of graduating in a recession. Am. Econ. J. 4 (1), 1–29.
Visser, J., 2013. Data base on institutional characteristics of trade unions, wage setting, state intervention and social pacts, 1960–2011 (ICTWSS)," - version 4.0.
Wiswall, M., Zafar, B., 2015. How do college students respond to public information about earnings? J. Hum. Cap. 19 (2), 117–169.
Zafar, B., 2013. College major choice and the gender gap. J. Hum. Resour. 48 (3), 545–595.