Changes in Returns to Multidimensional Skills across Cohorts*

Lorenzo Navarini†

Job Market Paper

Link to latest version

August 2023

Abstract

From 1984 to 2020 in Germany, I document a significant decline in routine and a substantial increase in social tasks. Using a novel dynamic model incorporating endogenous skills and exogenous ability, I estimate changes in returns to multidimensional skills. I find increasing returns to social skills aligning with the growing demand for social tasks. However, as non-cognitive skills, i.e. diligence, hold a comparative advantage in performing routine tasks, I find decreasing returns to non-cognitive skills and an offsetting effect on increasing returns to social skills. I show that routine task displacement harms individuals with low cognitive, low social and high non-cognitive skills.

*I express my profound gratitude to Dieter Verhaest, Olivier De Groote, Koen Declercq, and Jo Van Biesebroeck for their guidance and support. This paper benefited greatly from helpful comments at various stages from Christophe Bruneel-Zupanc, Kristof De Witte, Frank Verboven, Hannah Zillessen, Gregory Veramendi, Costas Meghir, and several audiences at KU Leuven, UCLouvain and others. Funding for this project was generously provided by the Research Foundation Flanders (FWO) - G079420N.

†KU Leuven, ECON Research Group, campus Brussels; Leuven Economics of Education Research (LEER); Email: lorenzo.navarini@kuleuven.be; Website: lorenzonavarini.com

1 Introduction

The widespread adoption of new technologies, organizational restructuring resulting from outsourcing and globalization, and a remarkable educational expansion have led to profound shifts in the demand and supply of skills and their dynamics. These phenomena have spurred extensive research in economics over the past few decades (Acemoglu and Autor, 2011; Deming, 2023). Despite a significant educational expansion, the returns to skills have continued to grow over the last decades as a result of "skill-biased" technology complementing high-skilled workers while replacing low-skilled workers (Tinbergen, 1974, 1975; Levy et al., 1992; Goldin and Katz, 2008; Acemoglu and Autor, 2011). However, advanced economies have also witnessed polarization in earnings and employment levels across the distribution of workers, with significant increases at both ends of the distribution and a decline in the middle (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Handel, 2013). Moreover, a growing literature on multidimensional skills has found decreasing returns to cognitive skills, despite increasing returns to education, along with increasing returns to social skills (Castex and Kogan-Dechter, 2014; Deming, 2017; Ashworth et al., 2021; Edin et al., 2022; Deming, 2023). At last, using a multidimensional approach to measuring skills has proven essential in examining heterogeneous returns to education, complementarities and mismatch costs (Rodríguez et al., 2016; Humphries et al., 2019; Guvenen et al., 2020; Lise and Postel-Vinay, 2020). As trends on changing returns to multidimensional skills cannot be explained simply by using the canonical model, Acemoglu and Autor (2011) and later Deming (2017, 2023) have offered novel theoretical frameworks to understand these trends better.

In this paper, I analyze changes in the task content of occupations in Germany between 1984 and 2020 while estimating the returns to multidimensional skills across cohorts using a dynamic model of joint educational choices and labour market outcomes. This model treats skills, measured at age 17, as endogenous to previous schooling while accounting for dynamic selection and unobserved heterogeneity, with the latter interpreted as exogenous ability. This is one of the first papers to estimate the returns to endogenous skills, which can be modified by schooling or other interventions, while controlling for exogenous ability, which is, by definition, not modifiable. At last, I estimate a model of occupational sorting using multidimensional skills and the task content of occupations. Overall, I explain that these findings confirm the theoretical framework of Acemoglu and Autor (2011) and

Deming (2017).

I contribute to the literature on the task-based approach and multidimensional skills. First, I develop a new measure of task content using data from the European Skills, Competences, Qualifications and Occupations (ESCO), which provides detailed task descriptions for occupations in Europe. Unlike studies relying on a limited number of questions from employer surveys, i.e. O*NET, my approach incorporates an extensive list of thousands of objective task measures. Using a latent factor approach, I categorize the task content of occupations into routine, social, and non-routine analytical (cognitive) tasks, controlling for measurement error (Deming, 2017). Moreover, ESCO is context-specific and readily applicable for cross-national analyses in Europe. This differs from papers, such as Edin et al. (2022) or Aghion et al. (2022), using O*NET for European countries. Second, I employ a dynamic model with endogenous multidimensional skills and exogenous abilities using data from the German Socio-Economic Panel (GSOEP). This approach allows me to identify changes in returns to endogenous skills, together with direct and total effects estimation, heterogeneous returns to skills, and complementarities. I utilize around 150 measures from a questionnaire distributed among a representative sample of the German population to extract multidimensional skills, including cognitive, social, and non-cognitive skills (Heckman et al., 2006; Cunha et al., 2010; Humphries et al., 2019; Ashworth et al., 2021; Toppeta, 2022). The measures used include standardized cognitive tests, GPA, parental involvement, courses in secondary schooling, extracurricular activities, time allocation to activities, satisfaction, self-confidence, personality traits, risk and time preference, trust measures, locus of control, and other indicators such as the number of close friends (Humphries and Kosse, 2017). I identify unobserved heterogeneity, i.e. exogenous ability, using initial conditions, local labour market conditions, a set of exclusion restrictions, including school recommendations and reforms in Germany, and the panel structure of the data.

I document significant changes in the task content of occupations and returns to multidimensional skills in Germany from 1984 to 2020. Using data from ESCO and GSOEP, I find evidence of the growing importance of social task content and a decline in routine task content. Non-routine analytical (cognitive) task content remained fairly stable, but the demand for cognitive tasks experienced a decline since the 2000s. Employment demand surged for occupations emphasizing social skills, regardless of their cognitive task content. A rise in demand for occupations intensive in a specific task will increase returns to individuals with a comparative advantage in performing these tasks (Acemoglu and Autor, 2011). Using a dynamic model, I find a large and significant increase of 6.4 percentage points in the returns to social skills across cohorts. At the same time, there were no significant changes in the returns to cognitive skills. Most importantly, I document a negative change in return to non-cognitive skills. Individuals with high non-cognitive skills drive this result since they hold a comparative advantage in routine-intensive occupations. Moreover, these individuals have no significant increasing returns to social skills. Low-cognitive individuals are better off developing higher social skills over high non-cognitive skills. At last, I find a strong complementarity between social and cognitive skills at the upper tail of the skill distribution. These trends align with the predictions of Acemoglu and Autor (2011) and are consistent with the growing importance of social skills in the labor market (Deming, 2017; Edin et al., 2022). Moreover, wage changes are closely connected to task displacement for a given group (Acemoglu and Restrepo, 2022): in this paper, I show that routine task displacement primarily harms individuals with low cognitive, low social and high non-cognitive skills. Finally, my model allows me to analyze the development of multidimensional skills. I find that secondary education grade retention negatively impacts cognitive and non-cognitive skills development without affecting social skills. In contrast, grade retention in primary education hurts all measures of skills, suggesting that social skills may follow a different development trajectory compared to cognitive and non-cognitive skills.

Related Literature

This paper relates and contributes to several branches of the literature. I contribute to a long-standing literature investigating the impact of technological change on the labor market. The concept of skill-biased technological change (SBTC), introduced in a series of papers starting from the early 1990s, defines a change in technology that complements skilled workers while substituting unskilled ones (Bound et al., 1992; Levy et al., 1992; Juhn et al., 1993; Goldin and Katz, 2008; Acemoglu and Autor, 2011). I contribute to this literature by connecting the task-based approach to the literature on changes in returns to multidimensional skills. There is a limited number of papers doing this from an empirical perspective. One model that addresses this link is presented by Acemoglu and

Autor (2011), which introduces a mapping between tasks and skills, considering the latter as individual endowments used to perform tasks. This framework categorises workers into high, medium, and low-skilled. Another valuable contribution by Deming (2017) involves both theoretical and empirical investigations of the growing importance of social skills and social task-intensive occupations. Furthermore, Deming (2023) provides a relevant review closely connected to my paper, presenting an overview of papers related to technology, tasks, and skills while emphasizing the importance of considering multidimensional human capital. Building upon the connection of these two literature, I contribute to both. First, I contribute to the literature on the task-based approach. Several papers have documented the process of employment polarization by extending the standard model and differentiating between skills and tasks while explaining it using various hypotheses such as routinization, structural change, and globalization (Autor et al., 2003; Autor et al., 2006; Acemoglu and Autor, 2011; Autor and Handel, 2013; Goos et al., 2014; Bárány and Siegel, 2018; Acemoglu and Restrepo, 2022). This phenomenon has been observed in the US and Europe (Goos and Manning, 2007; Dustmann et al., 2009; Goos et al., 2009, 2014). Spitz-Oener (2006), Rohrbach-Schmidt and Tiemann (2013), and Koomen and Backes-Gellner (2022) have measured the task content of occupations and the relative changes in Germany. In my paper, I contribute to this literature by developing a new measure of task content using data from ESCO and employing a latent factor approach. This objective measure can be complemented with subjective measures used in previous studies, such as the BIBB/IAB and BIBB/BAuA Employment Surveys on Qualification and Working Conditions in Germany. Additionally, this measure could serve as an objective benchmark for European countries, facilitating cross-national comparisons. Second, I contribute to the literature on multidimensional human capital (Heckman et al., 2006; Heckman et al., 2018b; Humphries et al., 2019; Attanasio, Blundell, et al., 2020; Attanasio, Cattan, et al., 2020; Toppeta, 2022) and changes in returns to multidimensional skills (Lundberg, 2013; Castex and Kogan-Dechter, 2014; Beaudry et al., 2016; Deming, 2017; Ashworth et al., 2021; Edin et al., 2022). Several papers have investigated the role of non-cognitive skills and personality traits on labour market returns (Heckman et al., 2006; Lindqvist and Vestman, 2011; Humphries and Kosse, 2017; Humphries et al., 2019; Guvenen et al., 2020; Lise and Postel-Vinay, 2020; Todd and Zhang, 2020). Moreover, other papers have provided evidence of changes in returns to a set of multidimensional skills: together with increasing returns to education (Ashworth et al., 2021; Blundell et al., 2021), there are decreasing returns to cognitive skills (Castex and Kogan-Dechter, 2014; Beaudry et al., 2016), and increasing returns to social skills (Deming, 2017; Ashworth et al., 2021; Edin et al., 2022). Our results also speak to the relatively few studies focusing on the rising complementarity between cognitive and social skills (Borghans et al., 2014; Weinberger, 2014; Deming, 2017). I contribute to this literature by implementing a measurement system that extracts three latent factors from a large set of 150 measurements (Humphries and Kosse, 2017). These endogenous multidimensional skills are measured at the age of 17 and are incorporated into a dynamic model, accounting for dynamic selection and unobserved heterogeneity, i.e. exogenous ability. Because of this, my paper is also closely connected to the literature on dynamic models of human capital accumulation, educational choices and labour market outcomes, starting from the seminal papers of Cameron and Heckman (1998, 2001). This paper uses a flexible dynamic discrete choice model developed by the dynamic treatment effects literature (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Ashworth et al., 2021). This approach has been applied by, among others, Colding et al. (2006), Belzil and Poinas (2010), Ashworth et al. (2021), De Groote (2022), Neyt et al. (2022), and Navarini and Verhaest (2023). A set of papers have introduced multidimensional skills in dynamic models (Humphries et al., 2019; Guvenen et al., 2020; Lise and Postel-Vinay, 2020) and estimated changes to returns across cohorts using a dynamic model (Ashworth et al., 2021). Ashworth et al. (2021) is a closely related paper, as it estimates a dynamic model for two cohorts while considering changes in returns to cognitive and non-cognitive skills. In my paper, however, I model skills as endogenous to schooling choices while accounting for innate ability. At last, using a dynamic model, I take a stance on the development of multidimensional skills. This contributes to the large literature on skill development (Cunha and Heckman, 2008; Cunha et al., 2010; Agostinelli and Wiswall, 2016; Heckman and Raut, 2016; Agostinelli et al., 2020; Sorrenti et al., 2020).

The rest of the paper is organised as follows. Section 2 introduces the data and describes the institutional context. Section 3 describes the model and the method to identify changes in returns to skill across cohorts. Section 4 includes the results of the model. Section 5 presents a series of robustness checks. At last, Section 6 concludes the paper.

2 Institutional Context and Data

This section describes the institutional context of Germany and introduces the data. I use two primary sources of data: ESCO and GSOEP. Further details about the data are discussed in Section A of the Appendix.

2.1 Institutional Context

In Germany, the compulsory education system covers the age range from 5 or 6 years old up to 18 years old. Primary school (*Grundschule*), which typically lasts for four years (six years in Berlin and Brandenburg), provides a fundamental education in subjects such as mathematics and German, as well as various science and social subjects. Students usually receive instruction in all main subjects from a single teacher during this stage. Students may repeat a grade both in primary and secondary education. One-fifth of all students (20.3%) in Germany experience grade retention and repetition during their school career, and it is above the average rate in OECD countries (i.e., 12.4% of all students, OECD, 2013). Upon completion of primary school, students move on to secondary school. At this point, schools recommend a specific type of secondary school for the students based on their grades, attitudes, and previous performance. Individuals may receive a lower, intermediate, or upper secondary schooling recommendation based on their early schooling performances in primary education.[1] In some federal states, these recommendations are mandatory, meaning that students cannot easily transition to a different type of secondary school from the one recommended. However, in other states, families are not bound by these recommendations and have more freedom to choose the secondary school type for their child. Over the last decades, federal states in Germany have substantially changed the role of school recommendations with federal reforms to binding school recommendations. Since the general adoption of teacher recommendations, states have frequently reformed their binding nature: several states have abolished binding recommendations to replace them with non-binding ones, and vice versa while other states have switched back and forth (Grewenig, 2022). At this stage, children are assigned to one of three distinct educational paths: the lower (basic) track (*Hauptschulabschluss*), the intermediate track (*Realschulabschluss*), or the upper (academic) track, which extends until grade 13 (or

[1] Some individuals may not receive a recommendation, or I may not observe the recommendation of individuals in the dataset, see Appendix A.2.

12) and leads to the university entrance qualification known as *Abitur*. The lower and intermediate tracks prepare students for vocational training or other practical forms of education. Therefore, different tracks have a differential effect on skill development, with certain tracks supporting the development of specific skills. While many school models now integrate lower and intermediate tracks, the upper track is primarily offered by *Gymnasium*, a school with an academic focus. Although it is possible to switch to higher-track schools, it is relatively uncommon. In 2000, only 1.5 percent of students switched to a higher track between grades 5 and 9 (Grewenig, 2022). After completing the lower or middle track, students typically enter a vocational training course, most commonly an apprenticeship. Apprenticeship training is often necessary for entry into specific skilled jobs. Moreover, two distinctive types of higher education institutions exist in Germany: universities for higher-level tertiary education and technical colleges (Fachhochschule) for lower-level.

2.2 Data

ESCO

The ESCO is a multilingual dictionary of skill requirements and task content of occupation, developed by the European Commission. It contains information on 3,008 occupations (ISCO-08) based on 13,890 skill requirements and relative descriptions. These narrower skill descriptions are included in broader skill groups. I reduce the dimensionality of this data by extracting three factors, used to describe the task content of each occupation. I interpret these factors as three key indicators of task content, following Deming (2017): routine, non-routine analytical (cognitive), and social tasks. Section A.1 in the Appendix includes a detailed description of the latent factors approach used and of alternative measures, used in Section D.1, as a robustness check. I link the resulting classification to the German Socio-Economic Panel (GSOEP), which includes panel data from 1984 to 2020 in Germany. Using ESCO and GSOEP together, I investigate the changes in the task content of occupations over this period. Table 1 includes a set of the top 10 ISCO-08 occupations sorted based on task content. For instance, occupations intensive in social skills are, among others: "Policy administration professionals", "Sports, recreation and cultural centre managers", as well as "Advertising and marketing professionals". Occupations with a high content of routine tasks are, for instance: "Metal working machine tool setters and operators" or "Mechanical engineering technicians". Last, occupations with high cognitive task content are: "University and higher education teachers", "Industrial and production engineers" and "Electronics engineers".

Table 1: Top 10 ISCO-08 Occupations by Factor of Task Content

Social	**Routine**	**Cognitive**
1349-Professional services managers not elsewhere classified	3115-Mechanical engineering technicians	2149-Engineering professionals not elsewhere classified
2310-University and higher education teachers	3119-Physical and engineering science technicians not elsewhere classified	1349-Professional services managers not elsewhere classified
2431-Advertising and marketing professionals	3123-Construction supervisors	2141-Industrial and production engineers
3435-Other artistic and cultural associate professionals	2149-Engineering professionals not elsewhere classified	3119-Physical and engineering science technicians not elsewhere classified
2131-Biologists, botanists, zoologists and related professionals	3114-Electronics engineering technicians	3115-Mechanical engineering technicians
2269-Health professionals not elsewhere classified	8142-Plastic products machine operators	1324-Supply, distribution and related managers
2422-Policy administration professionals	7223-Metal working machine tool setters and operators	2152-Electronics engineers
1431-Sports, recreation and cultural centre managers	7213-Sheet-metal workers	2144-Mechanical engineers
2141-Industrial and production engineers	8219-Assemblers not elsewhere classified	2310-University and higher education teachers
1324-Supply, distribution and related managers	8212-Electrical and electronic equipment assemblers	1223-Research and development managers

Notes: I sort ISCO08 4 digits occupations by using the latent factors. This table includes the top 10 occupations sorted by each latent factors.

GSOEP

The German Socio-Economic Panel (GSOEP) is a longitudinal micro-dataset containing a large number of individuals and households in Germany and was started in 1984. In this paper, I use the version of the data set that includes years up to 2020 (wave 37, SOEP, 2022). Beginning in 2000, a Youth questionnaire was administered to all young people at the age of 17, which contained specific questions about education and aspirations as they were being interviewed for the first time. Moreover, the GSOEP includes a set of standardized tests in the data on cognitive tests and measures on non-cognitive skills.

The GSOEP's Youth Questionnaire contains data on 9,370 individuals, which can be complemented with subsequent individual questionnaires. Of the 9,370 individuals, data on potential cognitive performance is available for 4,055. These are individuals born between 1982 and 2003. A full description of how I construct my variables, including the factors measuring multidimensional skills, can be found in Section A.2 in the Appendix. To study the returns to multidimensional skills across cohorts, I utilize data on cognitive and non-cognitive skills included in the GSOEP (see also Humphries and Kosse, 2017). Regarding cognitive skills, I use the data on standardized tests from the COGDJ questionnaire (covering all three subsets, which are verbal, numerical, and figural abilities) and information on secondary schooling GPA, advanced courses in secondary education, and parental involvement in school.

Table 2: Measuerement System for Multidimensional Skills

Measures		θ^c	θ^{nc}	θ^{sc}
Cognitive tests (COGDJ)				
20 Analogies questions	b	x		
20 Arithemtic Operator questions	b	x		
20 Figures questions	b	x		
Youth Questionnaire (JUGENDL)				
GPA (German, Math, 1. Foreign language)	c	x		
Advanced Course (German, Math, 1. Foreign language)	b	x		
Support tutor	b	x		
Upper track preferred certificate	b	x		
Parents Show Interest In ... [7 questions]	b	x		
Involvement in school [11 questions]	b		x	x
How Often ... [12 questions]	c		x	x
Satisfaction With [4 questions]	c		x	x
Probability in %: .. [12 questions]	c		x	x
Willingness to take risks	c		x	x
Trust People [3 questions]	c		x	x
Have fun today, not think about tomorrow	c		x	x
Personal characteristics: work carefully	c		x	
Personal characteristics: communicative	c			x
Personal characteristics: ... [14 questions]	c		x	x
Frequency of Being ... [4 questions]	c		x	x
Political Interests	c		x	x
Locus of control [10 questions]	c		x	x
Amount Of Closed Friends	c		x	x

Notes: the second column includes a b for binary outcomes and a c for continuous ones. Measures in bold are used for identifying the latent factors (see more details in Section A in the Appendix). θ^c denotes a latent factor extracted using dedicated measures related to cognitive skills, while θ^{nc} and θ^{sc} are latent factors extracted by a set of measures related to non-cognitive skills, such as personal characteristics or locus of control. See details about latent factors and a detailed table with the full list of the measurement system in Section A.2.2 in the Appendix.

I use a large set of measures to identify two factors regarding non-cognitive skills. This allows the definition of two different factors: externalizing (social) and internalizing (non-cognitive) skills (Toppeta, 2022). This list of measures is summarized in Table 2 (for more information on the latent factors and the detailed list of measures, see A.2.2 in the Appendix). I denote latent factors with θ: θ^c, θ^{sc}, and θ^{nc} denotes respectively cognitive, social, and non-cognitive skills.[2] The latter measures diligence, conscientiousness, and

[2]Heckman et al. (2006) and Deming (2017) measure non-cognitive skills using a normalized average

internalized focus.[3] I study changes in returns across demographic cohorts and, therefore, I define two demographic cohorts: M, those born before 1995 (Millennials, following a definition of demographic cohorts), and Z, those born after 1995 (also known as Generation Z). See more details in Section A.2.1 in the Appendix.

2.3 Descriptives

Table 3: Exogenous variables

	(1) M (1982-1995) mean	SD	(2) Z (1996-2003) mean	SD
Sex	0.495	0.500	0.497	0.500
Migration Background	0.227	0.419	0.334	0.472
Born in Germany	0.940	0.237	0.862	0.345
Siblings	1.622	1.339	1.467	1.534
Birth Year	1989.106	4.085	1999.409	2.254
Father Upper Secondary Education	0.195	0.396	0.180	0.384
Mother Upper Secondary Education	0.176	0.381	0.177	0.382
Father University	0.155	0.362	0.141	0.348
Mother University	0.106	0.308	0.115	0.319
Father High-Skilled Occupation	0.498	0.500	0.391	0.488
Mother High-Skilled Occupation	0.353	0.478	0.333	0.471
Big or middle-sized city	0.399	0.490	0.336	0.472
West Germany	0.793	0.405	0.838	0.369
Observations	4936		4432	

Notes: M denotes Millennials (born between 1982 and 1995), wile Z includes individuals born in Generation Z (born between 1995 and 2003). Father and Mother Education denotes the proprtion of parents holding an *Abitur*, with an upper secondary schooling completed. Father and Mother University denotes the portion of parents who completed a university degree. Father and Mother High-Skilled Occupation denotes individuals with a parent in a occupation classified as high-skilled in GSOEP. Big or middle-sized city is relative to the city of residence of the individual at the age of 17. This Table is produced using the full Youth questionnaire at disposal.

Table 3 includes observed characteristics for individuals in the two demographic cohorts. I include a set of parental background characteristics to capture potential differences in parental early schooling investment: if a parent has an upper secondary schooling diploma, has a university degree, and holds a high-skilled occupation. I also include geographical characteristics for each individual: whether she resides in a big or middle-sized city (relative to a small city or rural area) and if she resides in West Germany. Skills

of the Rotter Locus of Control and the Rosenberg Self-Esteem scale. In this paper, I utilize a factor extracted from a large set of measures, including Locus of Control and a measure of Self-Esteem. The latter could be extracted from questions about the probability of future events.

[3] Table 21 in Appendix shows the correlation between these three factors and the 15 questions used for extracting the so-called Big 5 personality traits. As Table 21 shows, θ^{nc} strongly correlates with the following personal characteristics: working carefully and carrying out duties efficiently. On the other side, it is negatively correlated with being lazy. These are the Big 5 questions associated with conscientiousness: individuals high in this trait have self-discipline, are diligent, and are organized and prepared.

are measured using a set of low-dimensional latent factors extracted from a large set of measurements on both cognitive and non-cognitive skills (Heckman et al., 2006).

In Figure 1, I show the sorting and skill development patterns for individuals with different skills. Regarding θ^c, a clear pattern emerges in the sorting (or development) of individuals into the three secondary tracks. Those in the upper track exhibit a distribution that significantly surpasses the mean. In contrast, the intermediate track aligns closely with the mean, while the lower track falls notably below the mean in accordance with the designated characteristics of each track. This may result from high-cognitive individuals sorting in the upper track, while it may also be the result of a focus on cognitive skill development in upper tracks relative to other tracks. Regarding θ^{nc} and θ^{sc}, the sorting pattern aligns with the one observed for θ^c, but less strong and clear. Overall, individuals in the upper track show, on average, a larger skill dimension in all three multidimensional skills.

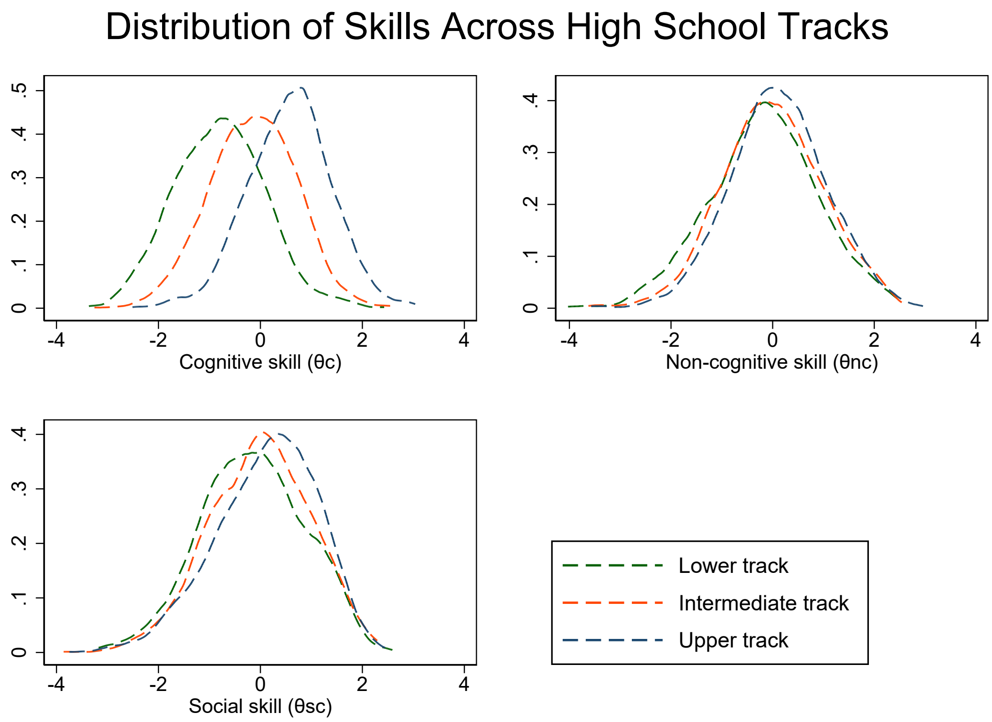


Figure 1: Distribution of Skills across High-School Tracks

Notes: details on the latent factors used in this Figure are included in A.2 in the Appendix. Latent factors θ are standardized to be mean 0 and standard deviation 1.

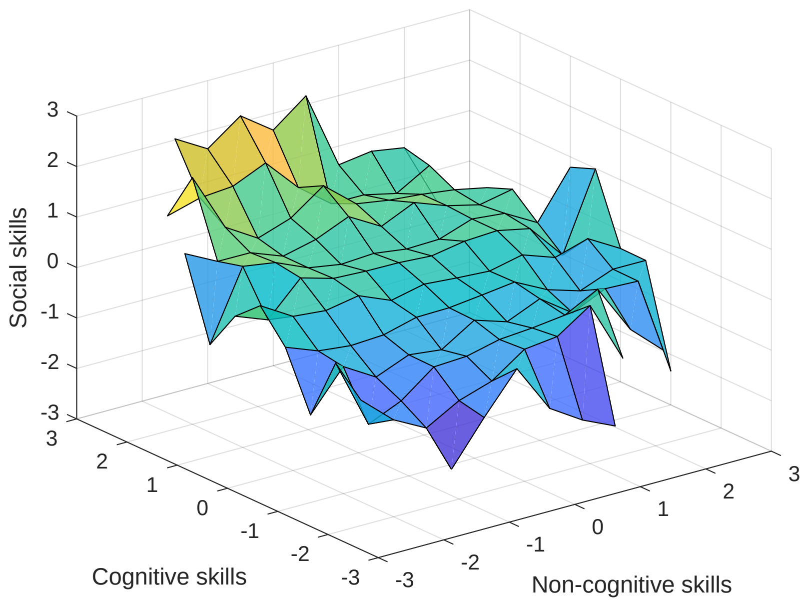


Figure 2: Relationship between Skills

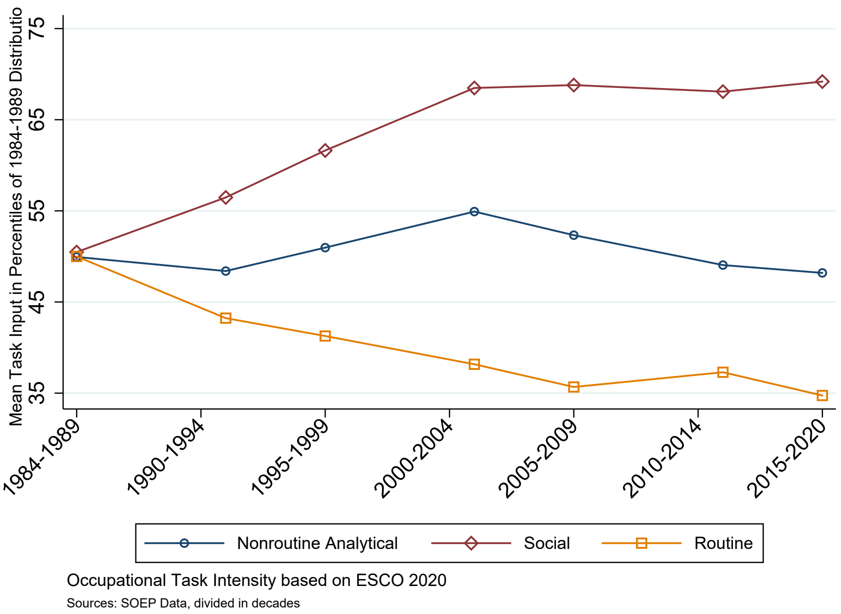
Notes: details on the latent factors used in this Figure are included in A.2 in the Appendix. Latent factors θ are standardized to be mean 0 and standard deviation 1.

Figure 2 illustrates the relationship between three distinct multidimensional skills. It reveals that individuals with high cognitive skills but low non-cognitive skills tend to exhibit higher social skills. Notably, social and non-cognitive skills represent distinct dimensions of skills, and individuals may focus on developing one dimension more than the other.

2.4 Changes in Tasks

Using data from ESCO and GSOEP, I estimate the changes in task content of occupation in Germany over the period 1984-2020. I start by presenting the trends in the task content of occupations and relative employment growth in Germany from 1984 to 2020. Considering the panel data nature of the GSOEP, I select the last available observation for individuals in each half-decade from 1984 to 2020. This results in a single observation per individual for each half-decade. Following Deming (2017) closely, I ensure that each task measure variable has a mean of 50 centiles in 1984 and the data are aggregated to the industry-education-sex level. This control for changes in the industry and labour supply in the German economy. Indeed, subsequent movements should be interpreted as changes in the employment-weighted mean of each task relative to its importance in 1984. Figure 3 replicates both Figure I from Autor et al. (2003) and Figure III from Deming (2017) using data from the GSOEP and the ESCO.

Figure 3: Worker Tasks in Germany, 1984-2020

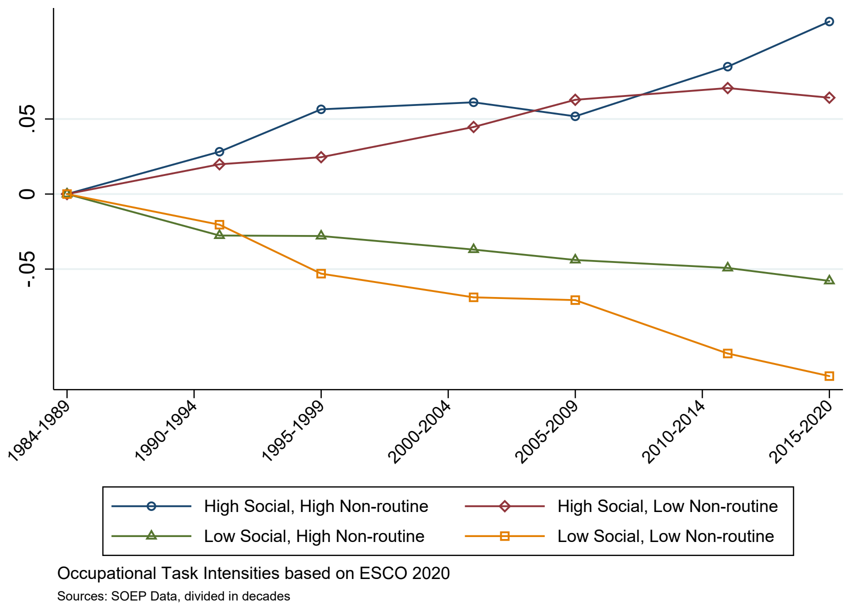


Notes: Figure 3 is constructed to parallel Figure I of Autor et al. (2003) and Figure III of Deming (2017), using data from Germany. Task measures are factors extracted by a large set of skill requirements and task descriptions by occupation (ESCO). See more details in Section B.2 in the Appendix. Data are aggregated to industry-education-sex cells by year, and each cell is assigned a value corresponding to its rank in the 1984 distribution of task input. Each task measure variable has a mean of 50 centiles in 1984. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year.

Overall, there has been a significant increase in social skill-intensive occupations. I find that the labour input of routine tasks has declined over this period. Routine skill task input declined by a stark -30%, comparable to the results of Deming (2017) for the US economy. The decline in routine tasks essentially mirrors the growing importance of social tasks in the labour force between 1984 and 2020 in Germany. Moreover, I find that, despite an initial increase in the task content of non-routine analytical (cognitive) between 1984 and the early 2000s, after 2000 this has declined and it is now at a stable level relative to 1984. Overall, this is consistent with the sharp decline of non-routine analytical (cognitive) task measures observed by Beaudry et al. (2016) in the United States starting from the early 2000s. I control for possible skill upgrading as a result of the high correlation between social and non-routine analytical (cognitive) skills task measures. I address this by dividing occupations into four categories based on whether they are above or below the median percentile in both non-routine analytical (cognitive) and social skill task intensity (see also Deming, 2017). I then compute the share of all labor supply-weighted employment in each category and year.

Figure 4 shows that occupations intensive in social tasks, regardless of their non-routine analytical task content, have grown over the period. Interestingly, between 1984 and 2009, there has been a convergence process, where high social, low non-routine analytical intensive occupations have grown more relative to high social, high non-routine occupations. However, from 2010 to 2020, this trend has reversed, with occupations intensive in high social and high non-routine analytical growing at the fastest pace. Concurrently, there has been a large decline in employment of low social, low non-routine intensive occupations. This is especially important in our setting, as it shows that there is a strong change in the demand for social and cognitive tasks between the early 2000s and the post-2010, which is the main division between the two demographic cohorts in the analysis.

Figure 4: Relative Changes by Occupation Task Intensity (1984-2020)



Notes: Each line plots 100 times the change in employment share (relative to a 1984 baseline) between 1894 and 2020 for occupations that are above and/or below the 50th percentile in non-routine analytical and social skill task intensity as measured by ESCO for the German economy. Source: GSOEP Data and ESCO.

2.5 Tasks and Skills: Theoretical Framework

By employing the theoretical framework put forth by Acemoglu and Autor (2011), it is possible to formulate several hypotheses regarding the returns on skills by examining the observed patterns of changes in the task content. Notably, this model offers a stark prediction. Suppose the relative market price of tasks where a particular skill group possesses a comparative advantage decreases. In that case, the relative wages of that skill group are expected to decline, regardless of whether the group reallocates its labor to a different set of tasks due to the shift in comparative advantage. In this setting, a large increase (decline) in the skill demand will produce a large increase (decline) in the relative market price. Indeed, as an example, Acemoglu and Autor (2011) consider a technological change that raises the productivity of high-skill workers in all tasks. The model's output is that high-skill workers would now perform some tasks formerly performed by middle-skilled workers. Relative wages paid to workers performing these (once) "middle-skill" tasks would increase since more productive high-skill workers now perform them. However, crucially, their analysis shows that the relative wage of medium-skill workers formerly performing these tasks would fall. In my paper, I do not consider measures of low to high-skilled workers, but I do consider workers with a bundle of multidimensional skills. The results are intuitively similar: e.g. individuals with high social skills have a comparative advantage in performing occupations intensive in social tasks. Considering these three task measures, we can assume that the relative market price of social tasks has increased over time, mirroring a large decline in the relative market price of routine tasks. As these tasks have become more (less) important in the labour force, there has been a greater (weaker) demand for individuals with a comparative advantage in performing these tasks. This generates increasing returns over time. Therefore, following the predictions of the model of Acemoglu and Autor (2011), I expect (i) an increase in the returns to social skills, as also predicted by the model of Deming (2017). However, other multidimensional skills play a role too. As the demand for non-routine analytical skill task measures has remained rather stable over the last decades, (ii) I do not expect a significant change in the returns to cognitive skills. At last, (iii) I expect a decline in the returns to non-cognitive skills, as individuals with high non-cognitive skills may have a comparative advantage in performing routine tasks. This is conditional on both social and cognitive skills. As non-cognitive skills, in my setting, are indicative of diligence, not being lazy, and conscientiousness, these hypotheses are in line with Heckman et al. (2006). Indeed, there is evidence that employers in low-skill labor markets value docility, dependability, and persistence more than cognitive ability or independent thought (Bowles and Gintis, 2002; Heckman et al., 2006). In this way, low-skilled and high-routine jobs may have strong wage returns to higher values of non-cognitive skills.

3 Identifying Returns to Multidimensional Skills

In this section, I develop a novel model that is a flexible dynamic discrete choice model, as developed by the dynamic treatment effects literature, incorporating both endogenous skills and exogenous ability (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Ashworth et al., 2021).

3.1 General Conceptual Framework

The GSOEP provides data on multidimensional skills for individuals aged 17. I refer to the period between primary education and age 17 as the schooling phase and the period between 17 and entry into the labor market as the school-to-work transition phase, as illustrated in Figure 5.

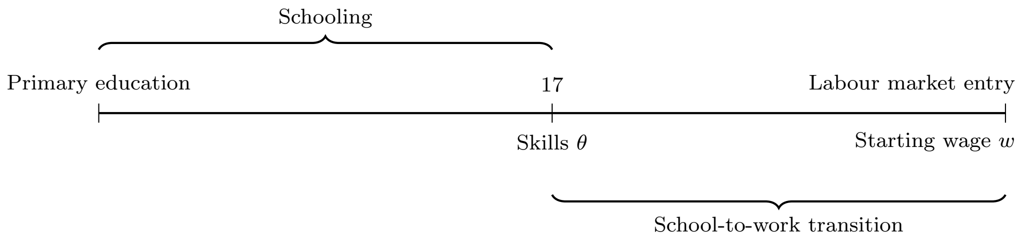


Figure 5: Timing

In my framework, I consider endogenous skills and exogenous abilities. Skills θ are endogenous to schooling choices and individual characteristics. This underlines the potential impact of environmental factors on skill development. I assume that individuals differ in their innate ability and exists a number $m \in M$ of unobserved types. Individuals have m-specific functions of skill development, schooling and labour market outcomes. Therefore, a general function, as in Equation 1, could represent skills θ^j for $j \in J$, with J representing a set of multidimensional skills:

$$\theta_i^j = f_m^{\theta^j}(X_i, f_m^s(X_i)), \tag{1}$$

where skills depend upon schooling choices, $f_m^s(X_i)$ and observed characteristics, X_i, including parental background. Once realized at the age of 17, multidimensional skills affect both post-compulsory education choices (after the age of 17), including the last years of secondary education and tertiary education choices, together with labour market outcomes. Therefore, from a general perspective, starting wages log(wage) could be modeled as a function of individual characteristics, X_i, schooling choices, f_m^s, multidimensional skills, θ_i^j and post-compulsory educational choices, f_m^e:

$$\log(wage)_i = f_m^w\Bigg(X_i, f_m^s(X_i), \theta_i^j, f_m^e\Bigg(X_i, f_m^s(X_i), \theta_i^j\Bigg)\Bigg), \tag{2}$$

where (2) is a general version of my benchmark model: skills and post-compulsory educational choices are also functions of previous variables. In this dynamic setting, skills θ_i^j not only directly influence wages but also have indirect effects through educational outcomes.

Using data from GSOEP, I can incorporate a broader range of variables during both periods to construct a model and estimate unobserved heterogeneity and returns to skills. The central insight recognises that choices made before measurement and individual characteristics, including parental background and location, influence skill development. This perspective aligns with contemporary findings in epigenetics, which emphasize the combined influence of genetics and the environment in shaping certain traits (Heckman, 2008). Furthermore, it is noteworthy that skills, which are realized at the age of 17, play a significant role in the decision to not drop out of secondary education, obtain a secondary diploma, and pursue enrolment and completion of tertiary education, before entering the labor market with a starting wage.

3.2 Model

I develop a sequential model of schooling decisions and labor market outcomes based on this general framework. Each individual $i \in I$, a member of demographic cohort c, undergoes a process of dynamic human capital accumulation. Following Ashworth et al. (2021), I estimate the model separately for each demographic cohort c. For the sake of clarity, I suppress subscript c in the subsequent equations, but the model should always be interpreted as cohort c specific.

I model choices from primary education to the entrance into the labour market. Let t denote the sequence of choices and outcomes in the model. Before skill measurement, I include a set of choices during the schooling phase, as shown in Figure 6. At $t = 1$, students repeat a grade in primary education or not, $D_1(\kappa_1)$, where $\kappa_1 \in \mathcal{K}_1 = \{0, 1\}$,

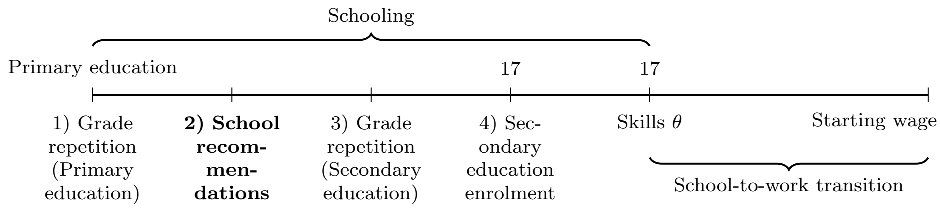


Figure 6: Model: Schooling Phase

with $\kappa_1 = 1$ defining repeating a grade. This depends upon time-unvarying observed characteristics (X_i) and t-specific local labour market conditions (L_{it}). Beyond X_i and L_{it}, I account for initial heterogeneity by introducing an additional state m, unobserved and persistent over time. This allows for correlation across the choices and outcomes of the model, accounting for unobserved heterogeneity and dynamic selection while relaxing i.i.d. assumptions. I assume the existence of $m = 1, ..., M$ types that differ in their preferences, skill development process, as well as educational and labour market productivity. At the end of primary education, individuals receive a school recommendation from schools and their teachers ($D_2(\kappa_2)$), as described in Section 2.1. Let $\kappa_2 \in \mathcal{K}_2 = \{0, 1, 2, 3\}$ denote, respectively, no recommendation, lower, intermediate and upper secondary education recommendation. At $t = 3$, individuals may repeat a grade in secondary education before the age of 17 ($D_3(\kappa_3)$). Grade repetition has largely long-term adverse effects, with lower chances of graduating from high school and possible long-term effects on skill development (Cockx et al., 2019). Upon skill measurement, individuals choose which track to enrol in secondary schooling, $D_4(\kappa_4)$ with $\kappa_4 = \kappa_2 \in \mathcal{K}_2$. After secondary school enrolment, at the age of 17, $t = \{5, 6, 7\}$, I include a set of multidimensional endogenous skills θ_i^j with $j \in \{c, nc, s\}$ denoting cognitive, non-cognitive and social skills. At this point, multidimensional skills θ_i^j, as measured at the age of 17, impact the likelihood of obtaining a specific secondary education diploma (or the relative probability of dropping out), enrolment and completion of a tertiary education degree. Consequently, these choices directly impact starting wages, as Figure 7 describes. Each skill θ_i^j for $j \in \{c, nc, s\}$ is endogenous into the dynamic model. These factors are estimated in a first stage, see further details in Section A.1.2 in the Appendix. Skills are latent factors extracted by 150 measurements, including standardized cognitive tests, personality traits and others. Each skill θ is the result of a development process that starts as early as schooling, and it includes parental and other individual characteristics, which can be interpreted as the effect of the environment on skills development. Moreover, local unemployment may influence skills development as an external shock. Skill development is also influenced by schooling choices and early schooling performances, such as grade retention or track enrolment.

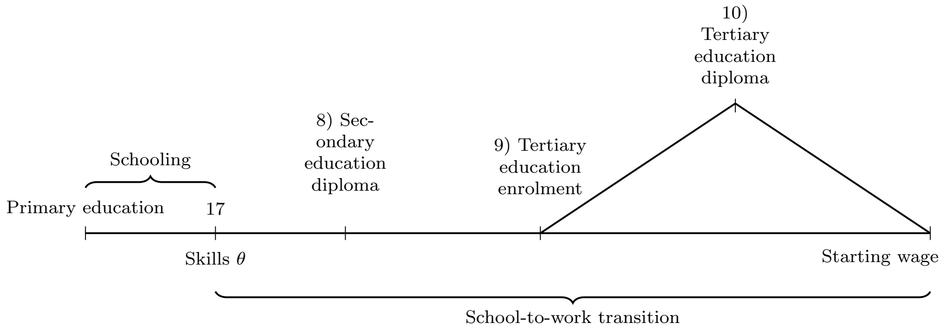


Figure 7: Model: School-to-work Transition

Higher cognitive and non-cognitive skill measures correlate with higher educational attainment and better outcomes. Individuals choose whether to obtain a secondary education diploma ($D_8(\kappa_8)$ with $\kappa_8 = \kappa_2 \in \mathcal{K}_2$). If students obtain a degree different than a lower secondary education ($D_8(\kappa_8) > 1$), they can enrol in tertiary education ($D_9(\kappa_9)$). After enroling ($D_9(\kappa_9) = 1$), they can obtain a diploma ($D_{10}(\kappa_{10})$). At last, individuals choose to enter the labour market after education ($D_{11}(\kappa_{11})$) and receive a starting log hourly wage ($t = 12$). $D_t(\mathcal{K}_t)$ for $t \in \{1, 3, 8, 9, 10, 11\}$ are binary choices, which are $\kappa_t = \kappa_1 \in \mathcal{K}_1 = \{0, 1\}$.

I use a flexible specification of the latent utility function regarding discrete choices. Let the latent utility function for individual i be denoted as $U_{it\kappa_t}$. $U_{it\kappa_t}$ depend on time-unvarying exogenous variables (X_i), time-varying local labour market conditions (L_{it}), t-specific endogenous outcomes (Z_{it}), and a residual term, v_{it}, that captures an unobserved component from the econometrician point of view. I approximate this latent utility function $U_{it\kappa_t}$ to be a linear function:

$$U_{it\kappa_t} = \beta_{0t} + \beta_{Xt} X_i + \beta_{Lt} L_{it} + \beta_{Zt} Z_{it} + v_{it} \text{ for } t \in \{1, 2, 3, 4, 8, ..., 11\} \tag{3}$$

The discrete choices of the model are characterized by the maximization of a latent variable $U_{it\kappa_t}$.

$$D_t(\mathcal{K}_t) = \underset{\kappa_t \in \mathcal{K}_\sqcup}{\text{argmax}} \left(U_{it\kappa_t} \right) \text{ for } t \in \{1, 2, 3, 4, 8, ...11\} \tag{4}$$

On the other hand, regarding continuous outcomes, which are skills and starting wages, I utilize a linear function:

$$Y_{it} = \beta_{0t} + \beta_{Xt} X_i + \beta_{Lt} L_{it} + \beta_{Zt} Z_{it} + v_{it} \text{ for } t \in \{5, 6, 7, 12\} \tag{5}$$

Log hourly wages $Y_{i12} = \log(wage)_i$ at the first job after the end of education are modelled as:

$$\log(wage)_i = \beta_{0t} + \beta_{Xt} X_i + \beta_{Lt} L_{it} + \beta_{Zt} Z_{it} + v_{it} \text{ for } t \in \{12\} \tag{6}$$

I use starting log hourly wages by removing the possible influence of endogenous work experience. Z_{i12} also includes a set of skill complementarities, dynamic complementarities with educational outcomes, and skill-ability complementarities.

3.3 Unobserved Heterogeneity and Identification

Unobserved heterogeneity is crucial in dynamic treatment effects models, because it induces correlation across different choices, addressing the issue of dynamic selection. This literature calls this matching on unobservables, relative to matching solely on observables (Heckman and Navarro, 2007). In this specific setting, exogenous unobserved heterogeneity may be considered a measure of ability, which defines a differential for individuals in developing skills and having improved schooling or labour market outcomes.[4] I apply the following factor structure to the error term v_{it}:

$$v_{it} = \gamma_{mt} \eta_m + \varepsilon_{it}, \tag{7}$$

in which η_m is a random effect, independent of ε_{it}, and independent across individuals, and in which γ_{mt} is an outcome-specific parameter related to this random effect. This random effect captures unobserved determinants and is assumed independent of the observed exogenous individual characteristics. Following the literature on dynamic discrete choice models, I use a finite mixture distribution to model the unobserved random variable

[4]Indeed, individuals are assumed to belong to one of the m unobserved types, and as such, they possess a type-specific constant that positively or negatively influences each outcome. For instance, individuals in the second unobserved type may have a positive unobserved factor (i.e., type-specific constant), resulting in higher average wages than individuals in the first unobserved type. This may be interpreted as individuals of the second type being more able, motivated, or productive in the work setting.

η_m (cf. Heckman and Singer, 1984; Arcidiacono, 2004).[5] I assume this distribution to be characterized by an a priori unknown number of M different heterogeneity types with type-specific heterogeneity parameters γ_{mt} for each outcome. This avoids relying on strong distributional assumptions and, therefore, also minimizes any bias resulting from misspecification in this respect (Heckman and Singer, 1984; Hotz et al., 2002).

I use a set of strategies to identify unobserved heterogeneity and correctly identify the model. First, the panel dimension of the data, specifically the autocorrelation of measured skills, educational choices, and wages given observed covariates, plays a crucial role in identifying the returns associated with skills while accounting for unobserved heterogeneity and dynamic selection. Secondly, including exclusion restrictions as variables that affect choices but are not included in the subsequent outcomes is crucial for addressing the selection bias, following Heckman and Navarro (2007), Heckman et al. (2016, 2018a, 2018b), and Ashworth et al. (2021). I impose exclusion restrictions during the schooling phase to identify exogenous ability, which is innate and assumed to impact all choices and outcomes in the model. I start with school recommendations influenced by the exogenous state-year variation in binding reforms made by federal states in Germany (Grewenig, 2022). For some pupils, recommendations they receive are binding: e.g. states with binding teacher recommendations have a selective tracking system since children can only attend academic schools if they have a recommendation. The effect of having either a binding or a non-binding system has an effect on how a teacher recommends a track. However, this does not affect future outcomes except through school recommendations. School recommendations are crucial in our model: they influence school track enrolment but do not influence later outcomes if not through school enrolment. There is a large unexplained variation among individuals who, for instance, received a lower school recommendation but still enrol in upper schooling and managed to develop higher skills, e.g. cognitive. In my model, unobserved heterogeneity captures this variation, and is interpreted as a source of ability differential among individuals. It reflects differences in factors such as grit, motivation, pure ability, and other aspects influencing skill development and future outcomes. School recommendation impacts school enrolment, as either way (binding or non-binding reforms), it will induce individuals into a specific track. Lastly, as the unemployment rate at the state level is a time-variant variable and t-specific, it works as

[5] It enters each likelihood contribution as a constant parameter, but, given the probability weight for each observation, it becomes a dummy capturing type-specific shocks.

an exclusion restriction for the subsequent outcomes (cf. Heckman et al., 2018a, 2018b; Ashworth et al., 2021). This is central in identifying the distribution of potential wages and the parameters from the realized wages of those employed in a first job (Ashworth et al., 2021).

3.4 Likelihood Function

I map each endogenous variable of the model to a likelihood function ℓ_{it}:

$$\ell_{it} = \begin{Bmatrix} \frac{1}{\sigma_o}\Phi(\frac{Y_{it}}{\sigma_o}) & \text{if continuous} \\ \Lambda(U_{it\kappa_t}) & \text{if discrete} \end{Bmatrix} \qquad \text{for } t \in T, \tag{8}$$

where the assumptions are that the idiosyncratic shocks (ε_{it}) for continuous variables are distributed $\mathcal{N}(0,1)$, and that binary and ordered outcomes have a type I extreme value distribution.

Without including unobserved heterogeneity ($v_{it} = \varepsilon_{it}$), the likelihood $\mathcal{L}_i$ of the model is constructed using the full set of outcomes and it is fully separable:

$$\log(\mathcal{L}_i) = \sum_{i=1}^{I} \log\left(\prod_{t=1}^{T} \ell_{it}\right) = \sum_{i=1}^{I}\sum_{t=1}^{T} \log(\ell_{it}) \tag{9}$$

Therefore, it can be estimated in separate stages, with consistent results.[6] However, when introducing unobserved heterogeneity ($v_{it} = \gamma_{mt}\eta_m + \varepsilon_{it}$), the likelihood is not separable anymore and the optimization issue becomes:

$$\{\hat{\gamma}, \hat{\pi}\} = \arg\max_{\gamma,\pi} \sum_{i=1}^{I} \left[\sum_{m=1}^{M} \pi_m \log\left(\prod_{t=1}^{T} \ell_{it}(H_t, \gamma_{mt}, \varepsilon_t)\right)\right], \tag{10}$$

where there is a number of M unobserved types, and I need to estimate both the probability types associated to each unobserved type m, π_m, and the m specific parameter for each outcome t. H_t includes at each stage X, L_t, Z_t. At this stage, the likelihood is not separable anymore because of the correlation induced by γ and π across different choices. I estimate this likelihood by using the Expectation Maximization (EM) Algorithm. More details about the estimation strategy using the EM Algorithm are included in Section

[6] This is by assuming that I do not have a problem of selection and, therefore, that earlier outcomes do not influence future outcomes.

B.1 in the Appendix. I evaluate the model optimization and the number of heterogeneity types in Section B.2 in the Appendix.

4 Results

Using the results from the cohort-specific models, I can compute different counterfactual simulations and retrieve the treatment effects. See Section B.3 in the Appendix for the definition of the treatment effects. See Section B.4 in the Appendix for further information on the simulations for estimating counterfactuals.

4.1 Changes in Returns to Skills

In this section, I estimate changes in the returns to skills across cohorts. I compare two demographic cohorts, M (1987-1995) and Z (1996-2003), and the analysis focuses on estimating the direct and total effects resulting from one standard deviation (σ) increase in cognitive, non-cognitive, and social skills.[7]

For each skill θ^j, with $j \in \{c, nc, sc\}$, I compute the direct, $g = direct$, and the total, $g = total$, effect of a σ increase in each skill:

$$\Delta^g_{\theta^j,c} = f^w_m(\theta^j_i + \sigma) - f^w_m(\theta^j_i) \tag{11}$$

Both direct and total returns, $\Delta^g_{\theta^j,d}$, are included in Table 4.

In general, I observe evidence of increasing returns to skills: from about a total (direct) return of 11.2% (5.2%) for individuals in M, I observe a total (direct) return of 18.7% (12.3%) for individuals in Z. Cognitive skills, θ^c, show the largest direct and total returns of, respectively: 4.4% and 10,5 % for individuals in M and 5.5% and 9% for individuals in Z. These are stable across cohorts. In both cases, the indirect effect of education is substantial: 6.1% for M and 3.5% for Z. Therefore, the importance of cognitive skills is also associated with increased access to further education, with returns through this channel. The returns to non-cognitive skills, θ^{nc}, conditional on both θ^c and θ^{sc}, are not significant. In terms of direct effects, non-cognitive skills are associated with a 2.5% wage return for demographic cohort M, while a negative return of -1.7% is associated with demographic

[7]Therefore, the effect should always be interpreted as the effect of one standard deviation (σ) increase of skills.

Table 4: Wage Returns to a σ Increase in Multidimensional Skills

	(1) M (1987-1995) Direct	Total	(2) Z (1996-2003) Direct	Total
Skills	0.052	0.112**	0.123*	0.187***
	(0.044)	(0.046)	(0.063)	(0.057)
Cognitive skills (θ^c)	0.044**	0.105***	0.055*	0.090***
	(0.020)	(0.022)	(0.030)	(0.030)
Non-cognitive skills (θ^{nc})	0.025	0.038	-0.017	0.007
	(0.018)	(0.023)	(0.028)	(0.029)
Social skills (θ^{sc})	0.021	0.002	0.056**	0.066**
	(0.020)	(0.025)	(0.027)	(0.029)

Notes: demographic cohort M includes individuals born between 1987 and 1995, while demographic cohort Z includes individuals born between 1996 and 2003. "Skills" is the combined return to a σ increase in all skills (θ^c, θ^{nc}, and θ^{sc}), including the effect of complementarities.

cohort Z. Interestingly, the returns to social skills are not significant for individuals in demographic cohort M, but become significant for individuals in demographic cohort Z: a σ increase in social skills is associated with a 6.6% increase in hourly wages for these individuals. Most of this effect is accounted for by direct effects, without considering the indirect effect of education. Therefore, this may be interpreted as a pure labour market change, as captured by the model of Deming (2017). These are total returns to education, controlling for unobserved heterogeneity, endogenous skill development and a set of observed characteristics.

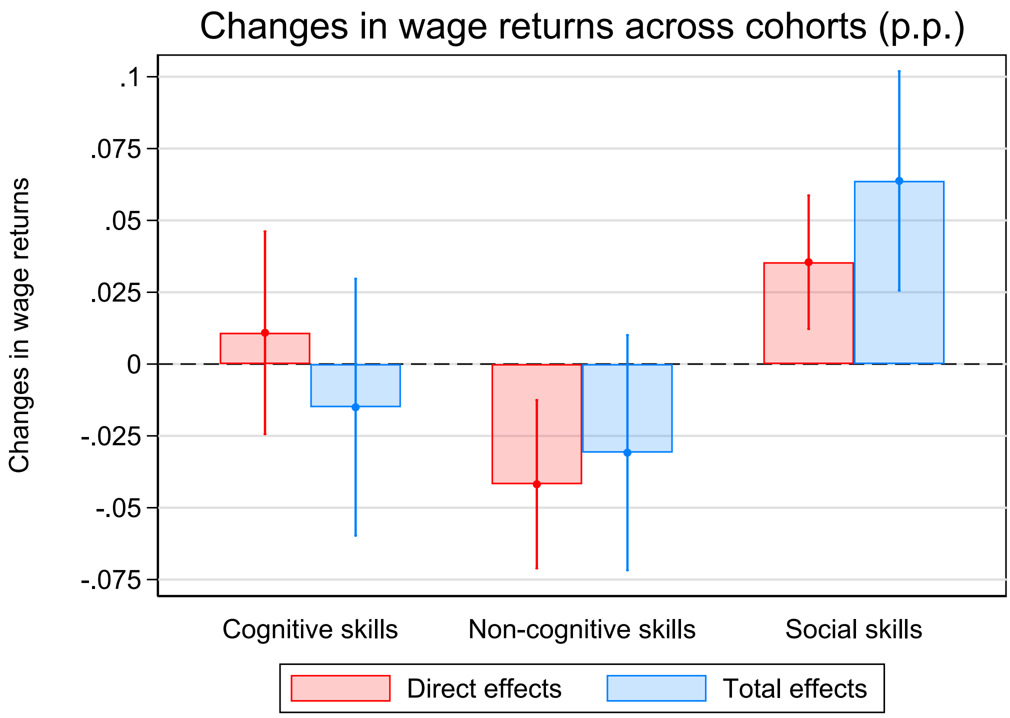
Using these returns, I can compare the changes across cohorts M and Z and simulate them by:

$$\Delta_a^g = \Delta_{a,Z}^g - \Delta_{a,M}^g \tag{12}$$

The results of this simulation are included in Figure 8. One of the major components driving increasing returns to skills is the higher returns to social skills, as predicted by Deming (2017).

Figure 8 shows the change in percentage points in wage returns to multidimensional skills across cohorts. Cognitive skills, as shown in Table 4, are stable over time, and I do not find evidence of a decreased return to cognitive skills. Moreover, I observe two interesting results. First, as predicted by the model of Deming (2017), the return to social skills has increased across these two cohorts. The return to total effects is associated with a change of 6.4 percentage points. Second, non-cognitive skills show a downward trend in

Figure 8: Changes in Wage Returns to Multidimensional Skills across Cohorts



Notes: Changes in wage returns are computed in percentage points (p.p.). This is the change computed across demographic cohorts.

wage returns, with direct effects implying a change of -4.2 percentage points for returns to a σ increase. These results largely align with the prediction made by the model of Acemoglu and Autor (2011) in Section 2.4. Indeed, increasing returns to skills are driven mainly by a significant increase in returns to social skills produced by the higher demand for individuals with a comparative advantage in performing social tasks. Moreover, I document decreasing returns to non-cognitive skills, which aligns with the significant decline in the demand for routine skill tasks. There is no significant change in returns to cognitive skills, as the demand for non-routine analytical (cognitive) skill tasks has remained relatively stable.

4.1.1 Changes in Complementarities

In this section, I compute further simulations to see how complementarities between multidimensional skills have changed over time. The model includes substantial heterogeneity and complementarities, both dynamic complementarities and skill complementarities: there are heterogenous returns to skill over the distribution. Indeed, I can estimate changes in returns considering selected bundles of skills. From Table 5, I find evidence

Table 5: Complementarities in Returns to Skills

	(1) M		(2) Z		(3) Z-M	
	Direct	Total	Direct	Total	Direct	Total
Complementarities: $\theta^c\theta^{nc}$	-0.026	-0.031	0.030	0.033	0.056**	0.065***
	(0.024)	(0.020)	(0.031)	(0.029)	(0.025)	(0.010)
Complementarities: $\theta^c\theta^{sc}$	-0.007	-0.006	-0.006	-0.005	0.001	0.002
	(0.027)	(0.022)	(0.029)	(0.026)	(0.024)	(0.007)

Notes: demographic cohort M includes individuals born between 1987 and 1995, while demographic cohort Z includes individuals born between 1996 and 2003. As in Deming (2017), I compute the complementarities between cognitive and non-cognitive as well as cognitive and social skills. In the simulation, I subtract the returns to a σ increase in both θ^c and θ^{nc} (or θ^{sc}), to the outcome of a combined σ increase in both skills. Using this approach, I can compute both direct and total effects.

of increasing returns to the complementarity between cognitive and non-cognitive skills. Conditional on social skills, increasing task complexity benefits individuals with both higher cognitive and higher non-cognitive skills as they can perform tasks more efficiently, even without "trading" tasks through social skills (Deming, 2017). I fail to find increasing complementarities between social and cognitive skills driven by heterogeneous returns to skills. I perform the following simulation to visualize the role of complementarities and their relative changes across cohorts. I compute the return to a σ increase in non-cognitive (θ^{nc}) and social (θ^{sc}) skills, given cognitive skills. More specifically, I compute for $j \in \{nc, sc\}$:

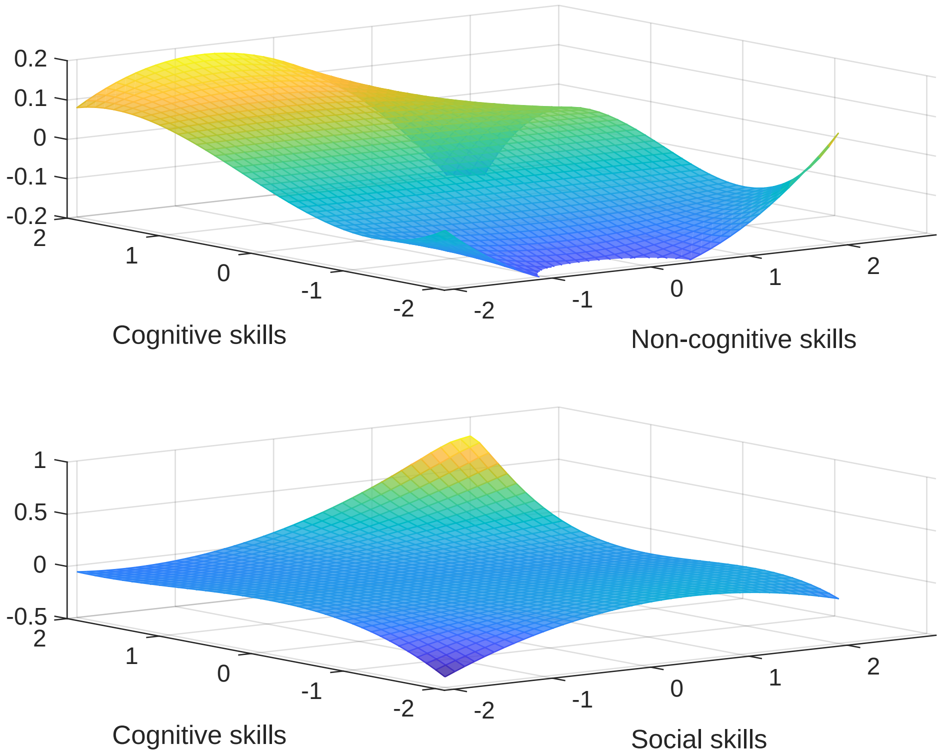
$$\Delta^{n,nn}_{\theta^j,\theta^c,\theta^{-j}} = \frac{1}{I}\sum_{i=1}^{I}\Bigg(\Big(f^w_{mZ}(\theta^j_{iZ} = nn+\sigma|\theta^c_Z = n, \bar{\theta}^{-j}_Z) - f^w_{mZ}(\theta^j_{iZ} = nn|\theta^c_Z = n, \bar{\theta} - Z^{-j})\Big) - \Big(f^w_{mM}(\theta^j_{iM} = nn+\sigma|\theta^c_M = n, \bar{\theta}^{-j}_M) - f^w_{mM}(\theta^j_{iZ} = nn|\theta^c_M = n, \bar{\theta}^{-j}_M)\Big)\Bigg), \quad (13)$$

where both n and nn are included in $\{-2, ..., 2\}$. In this formula, θ^{-j} represents the remaining skill, when considering θ^j (e.g. in the computation for θ^{nc}, $\theta^{-j} = \theta^{sc}$). The output is a matrix represented in Figure 9.[8]

Figure 9 shows two interesting results. First, as highlighted by the model in Deming (2017), there is a substantial increase in complementarities when job task complexity increases, as individuals who are more productive in both skills are also more able to trade tasks and be even more productive. Even if I fail to find significant results when

[8] With the dimensions of n and nn. As I include two vectors from -2 to 2, using intervals of 0.1, this is a 41x41 matrix.

Figure 9: Distribution of Changes in Wage Returns to a σ Increase across Cohorts



Notes: This graph is the result of a simulation for which we compute a σ increase at each point of the matrix computed using combinations of two skills while holding fixed the other skill (at mean). For each return, I compute the change across demographic cohorts. Skills are standardized to be distributed with mean 0 and standard deviation 1. All changes are expressed in percentage points.

considering the average treatment effect, it is clear that this is driven by the increasing returns on one side being cancelled out from the other side, individuals with low cognitive and social skills. This is evident from Figure 9, where the largest changes in the returns to θ^{sc}, are concentrated among θ^{c} and θ^{sc} above the mean. This is the complementarity between cognitive and social skills highlighted by the model presented in Deming (2017). Second, increasing complementarity between cognitive and non-cognitive skills is concentrated on the left side of the non-cognitive skill distribution. This means that individuals with high non-cognitive endowments do not benefit from increasing returns to skills. As shown in Figure 2, individuals with lower non-cognitive and higher cognitive skills are the ones with the largest social skills in the data. Conditional on having higher cognitive skills, individuals with greater non-cognitive skills do not benefit from increasing task complexity, as they prefer performing their own tasks over trading them. On the other hand, individuals with lower non-cognitive skills benefit the most from increasing task complexity: given increasing task complexity, these individuals may benefit from the increased capability of performing their own tasks efficiently, but with a higher propensity to trade them. This is clear from Figure 9, where the largest change in returns is concentrated between individuals with cognitive skills larger than 1σ and for individuals with non-cognitive skills comprised between -2σ and 0. The strongest change in returns is associated with high-skilled cognitive individuals but with non-cognitive skills below the mean. This mechanism could also be explained by Acemoglu and Autor (2011), as individuals who have a comparative advantage in routine tasks (high non-cognitive skills) essentially experience declining returns regardless of where they sort, as they have a comparative advantage to perform a set of tasks, which are declining.

This result highlights the importance of accounting for non-cognitive and social skills in analysing the impact of increasing job complexity and technological advancements. In Table 6, I show the heterogeneity in returns to a σ increase in each skill by considering different bundles of skills.[9]

The analysis of Table 6 reveals a substitution effect occurring within the distribution of non-cognitive skills: individuals with low non-cognitive skills are benefiting from the increasing returns to social skills, while those with high non-cognitive skills are experiencing a decline in their previously high returns to non-cognitive skills. This may be referred

[9] In Appendix C.1, I show Table 26, including the results for a different skill bundle, using θ^{sc}.

Table 6: Distribution of Changes Across Cohorts by Skill Bundle

		$\theta^{nc} < 0$				$\theta^{nc} > 0$			
		M (1987-1995)		Z (1996-2003)		M (1987-1995)		Z (1996-2003)	
		Direct	Total	Direct	Total	Direct	Total	Direct	Total
$\theta^c > 0$	Skills	0.017	0.076	0.142*	0.199**	0.102*	0.168***	0.149	0.211**
		(0.049)	(0.055)	(0.083)	(0.082)	(0.056)	(0.060)	(0.090)	(0.093)
	Cognitive skills θ^c	0.039*	0.100***	0.012	0.051	0.065**	0.121***	0.093**	0.130***
		(0.021)	(0.032)	(0.039)	(0.045)	(0.027)	(0.031)	(0.036)	(0.048)
	Non-cognitive skills θ^{nc}	-0.000	0.014	0.027	0.052	0.053**	0.070**	-0.006	0.015
		(0.021)	(0.034)	(0.036)	(0.043)	(0.026)	(0.035)	(0.041)	(0.050)
	Social skills θ^{sc}	0.016	-0.000	0.073**	0.085**	0.023	0.009	0.033	0.044
		(0.022)	(0.034)	(0.036)	(0.042)	(0.026)	(0.034)	(0.035)	(0.047)
$\theta^c < 0$	Skills	-0.007	0.042	0.107*	0.172***	0.108**	0.179***	0.112	0.179**
		(0.047)	(0.052)	(0.057)	(0.050)	(0.051)	(0.068)	(0.074)	(0.070)
	Cognitive skills θ^c	0.017	0.083**	0.015	0.049	0.056**	0.121***	0.101**	0.134***
		(0.025)	(0.033)	(0.038)	(0.038)	(0.028)	(0.046)	(0.039)	(0.042)
	Non-cognitive skills θ^{nc}	-0.005	0.001	-0.019	0.007	0.056**	0.071	-0.051	-0.027
		(0.025)	(0.034)	(0.033)	(0.035)	(0.026)	(0.050)	(0.041)	(0.044)
	Social skills θ^{sc}	0.018	-0.008	0.082**	0.091**	0.033	0.010	0.033	0.042
		(0.028)	(0.036)	(0.034)	(0.037)	(0.028)	(0.045)	(0.039)	(0.042)

Notes: This graph includes the treatment effects of a σ increase to each skill by different skill bundles.

to as an offsetting effect of high non-cognitive skills on the increasing returns to social skills. Individuals with lower non-cognitive skills experience a significant increase in the returns to social skills, which is not true for those with higher non-cognitive skills.

Table 7: Distribution of Changes Across Cohorts (High-cognitive)

	Changes in returns			
	$\theta^c > 0, \theta^{nc} < 0$		$\theta^c > 0, \theta^{nc} > 0$	
	Direct	Total	Direct	Total
Skills	0.125***	0.123**	0.046	0.043
	(0.048)	(0.057)	(0.051)	(0.061)
Cognitive skills θ^c	-0.027	-0.050	0.028	0.009
	(0.026)	(0.041)	(0.028)	(0.044)
Non-cognitive skills θ^{nc}	0.028	0.037	-0.059**	-0.055
	(0.024)	(0.043)	(0.025)	(0.042)
Social skills θ^{sc}	0.058***	0.086**	0.010	0.035
	(0.022)	(0.039)	(0.020)	(0.037)

Notes: For each return, I compute the change across demographic cohorts. Skills are standardized to be distributed with mean 0 and standard deviation 1. All changes are expressed in percentage points.

Table 7 shows the changes in percentage points for individuals with high cognitive skills. In this case, there is a strong change in returns for individuals with high cognitive and low non-cognitive. I do not find such a strong change in returns to social skills for individuals high in cognitive and non-cognitive skills. At last, individuals with high cognitive and non-cognitive skills experience a negative change in return to non-cognitive skills.

Table 8: Distribution of Changes Across Cohorts (Low-cognitive)

	Changes in returns			
	$\theta^c < 0, \theta^{nc} < 0$		$\theta^c < 0, \theta^{nc} > 0$	
	Direct	Total	Direct	Total
Skills	0.115***	0.130***	0.000	0.004
	(0.022)	(0.038)	(0.064)	(0.043)
Cognitive skills θ^c	-0.002	-0.034	0.013	0.045
	(0.017)	(0.034)	(0.053)	(0.031)
Non-cognitive skills θ^{nc}	-0.014	0.006	-0.098*	-0.108***
	(0.015)	(0.030)	(0.052)	(0.027)
Social skills θ^{sc}	0.064***	0.099***	0.032	0.000
	(0.013)	(0.030)	(0.049)	(0.022)

Notes: For each return, I compute the change across demographic cohorts. Skills are standardized to be distributed with mean 0 and standard deviation 1. All changes are expressed in percentage points.

I further investigate this finding in Table 8. I compute the same change in returns for individuals holding a skill bundle with low cognitive skills. Table 8 illustrates a noteworthy observation: the decline in returns to non-cognitive skills is even more pronounced among individuals with low levels of cognitive and high levels of non-cognitive skills. These individuals experience a significant decrease of 10.8 percentage points in return to non-cognitive skills. Interestingly, individuals with low cognitive abilities but high non-cognitive skills do not benefit from increasing returns to skills. They are also more likely to find themselves in low-skilled routine jobs. Individuals with lower levels of both cognitive and non-cognitive skills actually benefit considerably from the increasing returns to social skills. This leads to an overall rise in multidimensional skill returns, primarily driven by the increasing returns to social skills. Additionally, the offsetting effects of high non-cognitive skills remain consistent among individuals with low cognitive abilities.

Overall, these findings suggest that a bundle with high non-cognitive skills may not be associated with increasing returns to skills. This is most likely connected to the fact that conditional on social skills, individuals high in non-cognitive skills have a comparative advantage in performing routine tasks, as I empirically test in Section 4.1.2. This is the most important mechanism I offer to explain the negative change in returns to non-cognitive skills and its offsetting effects on increasing returns to social skills.

4.1.2 Occupational Sorting

The findings of previous sections are largely in line with the prediction of the model included in Acemoglu and Autor (2011). In this section, I show that individuals with high non-cognitive skills hold a comparative advantage in performing routine tasks. This explains why returns to non-cognitive skills have diminished, and a bundle with higher non-cognitive skills has an offsetting effect on increasing returns to skills. Using the task measures extracted from ESCO, I categorize each occupation with a binary variable indicating if it has a task content above the 50 percentile. Therefore, I estimate a single dynamic model by estimating the effects of a σ increase for a higher probability of sorting into an occupation that is task intensive in either social, routine, or cognitive. The results are included in Table 9.

Table 9: Occupational Sorting (Tasks and Skills)

	Occupational Sorting		
	Social	Routine	Cognitive
Cognitive skills (θ^c)	0.044**	0.023	**0.050*** **
	(0.017)	(0.018)	**(0.013)**
Non-cognitive skills (θ^{nc})	0.070***	**0.051*** **	0.074***
	(0.019)	**(0.016)**	(0.015)
Social skills (θ^s)	**0.084*** **	0.017	0.094***
	(0.017)	(0.016)	(0.012)

Notes: I classify each occupation with a binary outcome, where 1 defines an occupation with task content above the 50 percentile in either social, routine, or nonroutine analytical (cognitive) task. The model is re-estimated using these three binary outcomes at the place of starting wages.

Indeed, individuals with high non-cognitive skills have a large comparative advantage in performing routine tasks. A σ increase in non-cognitive skills generates a greater sorting into occupation intensive in routine tasks, which is not evidenced for other skills. This generates an overall reduction in returns to non-cognitive skills for all individuals, conditional on their bundle of skills. Therefore, we observe a large decline in wage returns to non-cognitive skills, especially for individuals with lower cognitive skills. Moreover, I observe an offsetting effect of non-cognitive skills on increasing returns to social skills: individuals with high non-cognitive skills do not experience an increasing return to these skills. This can be explained using the theoretical framework of Acemoglu and Autor (2011). Notably, while factor-augmenting technical progress always increases all wages in the canonical model, it can reduce the wages of certain groups in this more general model.

If the relative market price of the tasks in which a skill group holds comparative advantage declines, the relative wage of that skill group should also decline, even if the group reallocates its labor to a different set of tasks (i.e., due to the change in its comparative advantage).

4.2 Development of Multidimensional Skills

In this section, I estimate the returns to early schooling regarding skill development. It is clear, from both Deming (2017) and Deming (2023), that skill development for both θ^{nc} and θ^{sc} is a crucial topic of further research. Using my model, I can estimate a simple treatment effect for various early schooling outcomes on skills.

Table 10: Development of Multidimensional Skills

		M (1987-1995) Skills:			Z (1996-2003) Skills:		
	Grade retention:	Cognitive (θ^{c})	Non-cognitive (θ^{nc})	Social (θ^{sc})	Cognitive (θ^{c})	Non-cognitive (θ^{nc})	Social (θ^{sc})
ATE	Primary Education	-0.528***	-0.205**	**-0.189****	-0.800***	-0.402***	**-0.317*****
		(0.087)	(0.082)	**(0.094)**	(0.093)	(0.091)	**(0.103)**
	Secondary Education	-0.261***	-0.414***	**-0.003**	-0.228***	-0.233***	**0.069**
		(0.058)	(0.066)	**(0.058)**	(0.060)	(0.066)	**(0.066)**
ATT	Primary Education	-0.560***	-0.184**	**-0.145**	-0.754***	-0.427***	**-0.344*****
		(0.086)	(0.090)	**(0.090)**	(0.090)	(0.093)	**(0.092)**
	Secondary Education	-0.287***	-0.418***	**-0.058**	-0.265***	-0.246***	**0.031**
		(0.061)	(0.064)	**(0.061)**	(0.065)	(0.069)	**(0.071)**
ATNT	Primary Education	-0.526***	-0.206**	**-0.193****	-0.805***	-0.399***	**-0.314*****
		(0.089)	(0.083)	**(0.096)**	(0.097)	(0.095)	**(0.107)**
	Secondary Education	-0.256***	-0.413***	**0.007**	-0.222***	-0.231***	**0.076**
		(0.059)	(0.067)	**(0.060)**	(0.061)	(0.066)	**(0.066)**

Notes: causal estimates of the effects of grade retention on skill development using the dynamic model. Average Treatment Effects (ATE) computes the effect for the full population, Average Treament Effects on the Treated (ATT) computes the impact on individuals who have been retained in either primary or secondary education. Average Treatment Effects on the Non-Treated (ATNT) computes the impact for individuals who have never been retained in education. Effects are expressed in σ standard deviations.

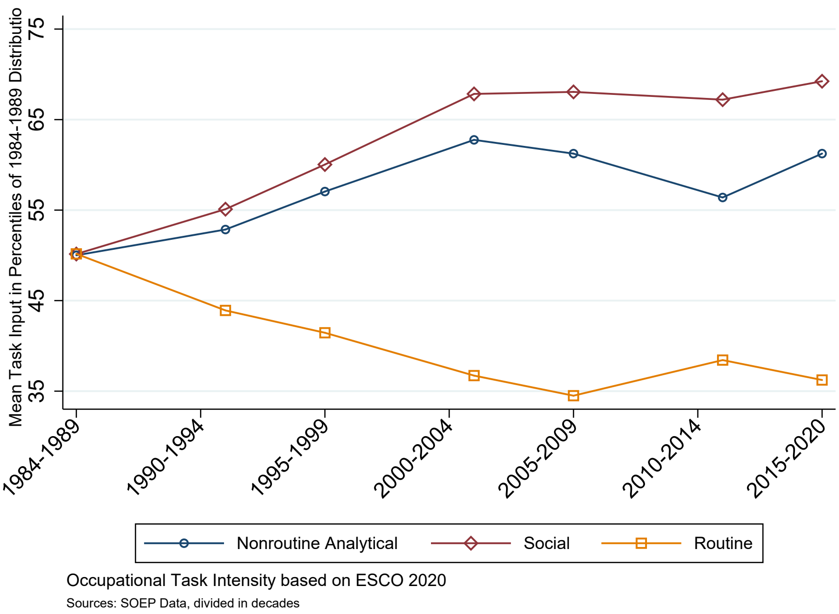
In Table 10, I estimate the treatment effects associated with grade retention in both primary and secondary education for both cohorts. In both cases, grade retention in primary and secondary education implies a large loss in both cognitive and non-cognitive skills: for demographic cohort M, respectively, 52% (26%) of a standard deviation for primary (secondary) education, while a 20% (41%) of an SD for primary (secondary) education. This is also in line with the results for demographic cohort Z: 80% (22%) of a standard deviation for primary (secondary) education for cognitive skills, while a 40% (23%) of an SD for primary (secondary) education for non-cognitive skills. The evidence on social skills is different. Grade retention in primary education generates a loss in social skills in both cohorts of around 18% of a σ and 31% of a σ. However, grade retention in secondary education does not generate any significant effect on social skills: for demographic cohort M the effect is close to zero, while for cohort Z, the effect is positive but insignificant.

5 Robustness Checks

5.1 Task Content without Latent Factors

As a first robustness check, in this subsection, I estimate the task content of each occupation without relying on latent factors but using continuous measurements. Each skill group is associated with a task by using broader skill groups, and these are aggregated into continuous measurements (then standardized) used for defining each occupation. The definition of these continuous measurements is included in Appendix, Section D.1. Figure 10 is produced with the same procedure as Figure 3, but using this continuous measurement.

Figure 10: Worker Tasks in Germany, 1984-2020



Overall, the patterns are similar, with occupation social skills intensive increasing substantially over the period. This is mirrored by a large decline in occupation intensive in routine tasks. The main difference relates to non-routine analytical task, that, using these measurements, seems to rise together with social tasks. In Figure 17, included in Appendix D.1, I perform again the same calculations of Figure 4, while using these continuous measurements. The results are, again, largely in line with the results of Figure

4. The only difference lies in the decline over the last half-decade for occupation intensive in social and non-routine tasks.

5.2 Changes in Present Value Earnings to Skills

In this paper, I use starting wages so to rule out the effect of different accumulation of work experience among individuals with different skill bundles. Moreover, I do not account for endogenous work experience accumulation. To check the robustness of my results on starting wages, I can also consider the adjusted present value of earnings, computed using all the observations on wages for each individual.

Table 11: Results using Average Present Value for Earnings

	(1) M		(2) Z		(2)-(1) Change	
	Direct	Total	Direct	Total	Direct	Total
Skills	0.114*	0.119	0.182*	0.186*	0.068	0.067
	(0.064)	(0.073)	(0.104)	(0.104)	(0.076)	(0.072)
Cognitive skills (θ^{c})	0.057**	0.053*	0.075	0.088	0.018	0.035
	(0.029)	(0.030)	(0.056)	(0.058)	(0.043)	(0.038)
Non-cognitive skills (θ^{nc})	0.011	0.015	0.017	0.014	0.005	-0.002
	(0.029)	(0.028)	(0.060)	(0.060)	(0.051)	(0.047)
Social skills (θ^{sc})	-0.011	-0.004	0.065	0.066	0.076	0.070
	(0.035)	(0.031)	(0.063)	(0.061)	(0.050)	(0.046)

The results are included in Table 11, with both direct and total returns from a σ increase in each skill and changes in percentage points across cohorts for each skill. The results are noisier in terms of precision, but they indicate similar conclusions, with an increase of around seven percentage points for returns to social skills and stable changes in returns to cognitive skills. The less precise estimates could be determined by the role of work experience in defining present value and the issue of attrition since I do not observe the same number of years after the starting wage for each individual.

5.3 Excluding Individuals by Year

The definition of the two demographic cohorts may appear arbitrary, and it is worth noting that individuals on the fringes of the cohort definition may have similar characteristics. To ensure the robustness of my results, I exclude individuals from the years that fall on the boundaries of the demographic cohort definition. Therefore, I exclude individuals born in 1994, 1995, and 1996. Afterwards, I re-estimate the model and analyze the outcomes, as presented in Table 12. This shows again a large increase in the returns to social skills, estimated to be around seven percentage points for the total returns. Overall, there are no sizeable changes for both cognitive and non-cognitive skills. The results are in line with Figure 8.

Table 12: Results Excluding Individuals by Year

	(1) Changes	
	Direct	Total
Cognitive skills (θ^c)	0.002	-0.039
	(0.026)	(0.029)
Non-cognitive skills (θ^{nc})	0.007	-0.011
	(0.016)	(0.023)
Social skills (θ^{sc})	0.049**	0.070***
	(0.021)	(0.026)

5.4 Changes in Returns to Multidimensional Skills

In this section of robustness checks, I estimate a model without using latent factors but by including a large set of multidimensional abilities, such as the Big 5 personality traits and other dimensions. This is a similar approach to what I perform for task content in Section 5.1. I begin with Table 13, where I compute the wage return to a σ increase for cognitive and non-cognitive skills.[10]

Table 13: Changes in Returns to Multidimensional Skills Across Cohorts

	(1) M		(2) Z		Changes in returns (2)-(1)	
	Direct	Total	Direct	Total	Direct	Total
Cognitive skills	0.036	0.121***	0.170***	0.194***	0.134***	0.073**
	(0.036)	(0.046)	(0.050)	(0.050)	(0.018)	(0.036)
Non-cognitive skills	0.030	0.006	0.095	0.151	0.064	0.146**
	(0.079)	(0.090)	(0.104)	(0.106)	(0.041)	(0.057)

Notes: I estimate the effect of a σ increase in all measures aggregated into broader measures of cognitive (including standardized tests and GPA) and non-cognitive skills (including the Big 5 personality traits, confidence, risk and time preferences).

[10]In this setting, I do a counterfactual scenario where there is a σ increase in each skill, included in either cognitive or non-cognitive skills.

While cognitive skills exhibit a clearly positive effect on both direct and total effects, the impact of non-cognitive skills is less evident. There is a 7.3 percentage point increase for cognitive skills, whereas non-cognitive skills exhibit a more significant increase of 14.6 percentage points. This represents a difference of nearly 7.3 percentage points, favouring non-cognitive skills over cognitive skills. On the other hand, when considering the change in direct effects without accounting for the impact of education, a strong increase of 13.4 percentage points is observed for cognitive skills, while the increase of 6.4 percentage points for non-cognitive skills is not statistically significant.

5.4.1 Changes in Returns to Cognitive

Figure 18 in Section D.2 in Appendix provides an overview of the changes in wage returns resulting from a σ increase in each cognitive skill across cohorts. When considering the total effects, both verbal and math abilities have a sustained return to skills across cohorts M and Z respectively: 5.48% vs. 4.6% for verbal and 6.5% vs. 6.5% for math. Analyzing changes across cohorts, there is no evidence of significant variations in total returns on these skills. The returns have remained relatively stable over the past decades. Indeed, when analyzing the direct effects, there is no observable change in verbal abilities (2.6% vs. 2.9%), whereas math abilities demonstrate a significant increase in returns (2.36% vs. 5.82%). The majority of changes regarding the returns on cognitive skills occurred at the labor market level, with minimal differences observed within the educational setting.

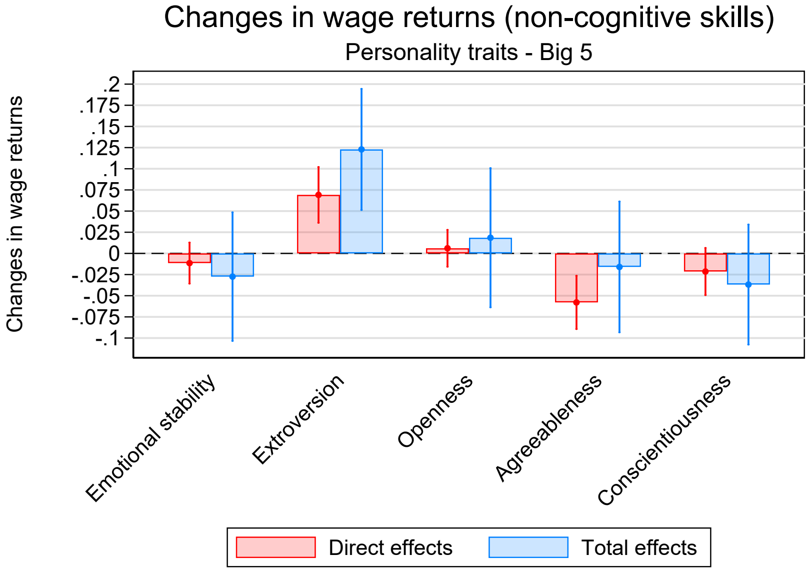
5.4.2 Changes in Returns to Non-Cognitive

Figure 11 includes the change across cohorts in returns to a σ increase in each skill.

When considering total effects, the sizeable increase in non-cognitive skills returns is mostly associated with extroversion, among personality traits. This validates our result using latent factors, as extroversion highly indicates greater social skills.[11] Relative to non-cognitive skills, conscientiousness is one of the personality traits mainly associated with my factor representing non-cognitive factors. This displays a downward trend, which is not significant. Results for other non-cognitive skills are contained in Section D.2 in Appendix.

[11]The latent factor interpreted as social skills is constructed by normalizing one of the measures for building the latent factor used in the Big 5 personality traits literature, measuring extroversion.

Figure 11: Changes in Wage Returns



Notes: Change, Δ_a^g, in wage returns across cohorts expressed in percentage points (p.p.). The change is the difference between cohort Z and M in the wage return to a σ increase in each specific skill. Direct effects do not include the indirect effects of education. Total effects include the composite effect of direct and indirect effects of a σ increase.

6 Conclusions

In this paper, I analyze the evolution of task content of occupations and changes in returns to multidimensional skills in Germany over a period from 1984 to 2020. I identify returns to multidimensional skills using a dynamic model of joint educational choices and labour market outcomes. In this model, skills are endogenous. To the best of my knowledge, this is one of the first papers estimating returns to endogenous skills while accounting for unobserved heterogeneity, interpreted as innate ability. This is important because schooling and other interventions may actually modify endogenous skills.

I employ a novel measure of task content based on ESCO. Using a latent factor approach, I reduce the dimensionality of this dataset and categorize occupations based on their task content in routine, social, and non-routine analytical (cognitive) tasks. Moreover, I estimate a dynamic model with endogenous multidimensional skills and exogenous abilities. I document a substantial change in the task content of occupations and in the returns to multidimensional skills in Germany over the period from 1984 to 2020. This shift is paralleled by a substantial decline in routine task content, while non-routine analytical (cognitive) task content remains relatively stable. I show a significant increase of 6.4 percentage points in the returns to social skills over this period. Conversely, there has not been any change in the returns to cognitive skills. At last, I document a negative change in returns to non-cognitive skills, conditional on cognitive and social skills. This is driven by individuals with high non-cognitive skills, especially low-cognitive-high-non-cognitive individuals. High non-cognitive skills offset increasing returns to skills: I find no evidence of increasing returns to social skills for individuals with high non-cognitive skills. This is especially true for low-cognitive individuals, indicating that low-cognitive-high-non-cognitive, having a strong comparative advantage in routine-intensive occupations, are particularly affected by these trends due to routine task displacement (Acemoglu and Restrepo, 2022). This is mainly in line with Deming (2017) and the growing importance of social skills in the labour market: over time, low-cognitive individuals are better off developing higher social skills than high non-cognitive skills. This is also in line with polarization, where low-cognitive, low-skilled workers are forced out from middle-skilled jobs, with a higher content of routine tasks, to low-skilled service jobs, with a high content of social tasks. More generally, I observe a substitution from high returns to non-cognitive skills to a high return to social skills. These findings are largely accounted for by the changes in skill demand of the German economy, considering comparative advantage and task intensity for each occupation, as shown using ESCO data. If the task content of routine jobs declines, individuals with a specific skill bundle, including high non-cognitive skills, who have a comparative advantage in performing these tasks, will be worse off. I also find a strong change in returns between social and cognitive skills at the upper tail of the skill distribution, highlighting a strong complementarity between these two skill dimensions. Lastly, I show that social skills may have a different development trajectory, rather than cognitive and non-cognitive skills, using findings on the effects of grade retention on skill development. In the future, as already highlighted by Deming (2017, 2023), there are promising topics to be examined on multidimensional human capital, such as the development of multidimensional skills, the impact of educational expansion (with a substantial effect on skill mismatch and overeducation), and the impact of novel technologies, such as artificial intelligence, which could replace cognitive tasks.

References

Acemoglu, D., & Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (pp. 1043–1171). Elsevier.

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in u.s. wage inequality. *Econometrica*, *90*(5), 1973–2016.

Achenbach, T. M. (1966). The classification of children's psychiatric symptoms: A factor-analytic study. *Psychological monographs*, *80*, 1–37.

Achenbach, T. M., Ivanova, M. Y., Rescorla, L. A., Turner, L. V., & Althoff, R. R. (2016). Internalizing/externalizing problems: Review and recommendations for clinical and research applications. *Journal of the American Academy of Child and Adolescent Psychiatry*, *55*, 647–656.

Aghion, P., Bergeaud, A., Blundell, R., & Griffith, R. (2022). Soft skills and the wage progression of low-educated workers. *Working Paper*.

Agostinelli, F., Doepke, M., Sorrenti, G., & Zilibotti, F. (2020). *It Takes a Village: The Economics of Parenting with Neighborhood and Peer Effects* (NBER Working Papers No. 27050). National Bureau of Economic Research, Inc.

Agostinelli, F., & Wiswall, M. (2016). Estimating the technology of children's skill formation. *NBER Working Paper No. 22442*.

Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, *130*, 1781–1824.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics*, *121*, 343–375.

Arcidiacono, P. (2005). Affirmative action in higher education: How do admission and financial aid rules affect future earnings? *Econometrica*, *73*(5), 1477–1524.

Arcidiacono, P., & Ellickson, P. B. (2011). Practical Methods for Estimation of Dynamic Discrete Choice Models. *Annual Review of Economics*, *3*(1), 363–394.

Arcidiacono, P., & Jones, J. B. (2003). Finite mixture distributions, sequential likelihood and the em algorithm. *Econometrica*, *71*, 933–946.

Arcidiacono, P., & Miller, R. A. (2011). Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica*, *79*, 1823–1867.

Ashworth, J., Hotz, V. J., & Maurel, A. (2021). Changes across cohorts in wage returns to schooling and early work experiences. *Journal of Labor Economics*, *39*, 931–964.

Attanasio, O., Blundell, R., Conti, G., & Mason, G. (2020). Inequality in socio-emotional skills: A cross-cohort comparison. *Journal of Public Economics*, *191*, 104171.

Attanasio, O., Cattan, S., Fitzsimons, E., Meghir, C., & Rubio-Codina, M. (2020). Estimating the production function for human capital: Results from a randomized controlled trial in colombia. *American Economic Review*, *110*, 48–85.

Autor, D. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspectives*, *29*, 3–30.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Reenen, J. V. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*, 645–709.

Autor, D., & Handel, M. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, *31*, S59–S96.

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*, 1279–1333.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of the u.s. labor market. *American Economic Review*, *96*(2), 189–194.

Baert, S., Neyt, B., Omey, E., & Verhaest, D. (2022). Student work during secondary education, educational achievement, and later employment: A dynamic approach. *Empirical Economics*, *63*, 1605–1635.

Bárány, Z. L., & Siegel, C. (2018). Job polarization and structural change. *American Economic Journal: Macroeconomics*, *10*(1), 57–89.

Beaudry, P., Doms, M., & Lewis, E. (2010). Should the personal computer be considered a technological revolution? evidence from u.s. metropolitan areas. *Journal of Political Economy*, *118*, 988–1036.

Beaudry, P., Green, D. A., & Sand, B. M. (2016). The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics*, *34*, S199–S247.

Belzil, C., & Poinas, F. (2010). Education and early career outcomes of second-generation immigrants in france. *Labour Economics*, *17*, 101–110.

Blundell, R., Green, D. A., & Jin, W. (2021). The u.k. as a technological follower: Higher education expansion and the college wage premium. *The Review of Economic Studies*, *89*(1), 142–180.

Borghans, L., Weel, B. T., & Weinberg, B. A. (2014). People skills and the labor-market outcomes of underrepresented groups. *ILR Review*, *67*(2), 287–334.

Bound, J., Johnson, G., Bound, J., & Johnson, G. (1992). Changes in the structure of wages in the 1980's: An evaluation of alternative explanations. *American Economic Review*, *82*, 371–92.

Bowles, S., & Gintis, H. (2002). Schooling in capitalist america revisited. *Sociology of Education*, *75*(1), 1–18.

Cameron, S. V., & Heckman, J. J. (1998). Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of american males. *Journal of Political Economy*, *106*, 262–333.

Cameron, S. V., & Heckman, J. J. (2001). The dynamics of educational attainment for black, hispanic, and white males. *Journal of Political Economy*, *109*, 455–499.

Castex, G., & Kogan-Dechter, E. (2014). The changing roles of education and ability in wage determination. *Journal of Labor Economics*, *32*, 685–710.

Cockx, B., Picchio, M., & Baert, S. (2019). Modeling the effects of grade retention in high school. *Journal of Applied Econometrics*, *34*, 403–424.

Colding, B., Colding, & Bjorg. (2006). A dynamic analysis of educational progression of children of immigrants. *Labour Economics*, *13*, 479–492.

Cunha, F., & Heckman, J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources*, *43*(4).

Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*, 883–931.

Dahmann, S., & Anger, S. (2014). *The Impact of Education on Personality: Evidence from a German High School Reform* (SOEPpapers on Multidisciplinary Panel Data Research No. 658). DIW Berlin, The German Socio-Economic Panel (SOEP).

De Groote, O. (2022). A dynamic model of effort choice in high school. *TSE Working Paper*, *19-1002*.

Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market*. *The Quarterly Journal of Economics*, *132*(4), 1593–1640.

Deming, D. J. (2023). Multidimensional human capital and the wage structure. *in preparation for the Handbook of the Economics of Education*.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the em algorithm. *Source: Journal of the Royal Statistical Society. Series B (Methodological)*, *39*, 1–38.

Dustmann, C., Ludsteck, J., & Schönberg, U. (2009). Revisiting the german wage structure. *The Quarterly Journal of Economics*, *124*(2), 843–881.

Edin, P. A., Fredriksson, P., Nybom, M., & Öckert, B. (2022). The rising return to noncognitive skill. *American Economic Journal: Applied Economics*, *14*, 78–100.

Goldin, C., & Katz, L. (2008). *The Race Between Education and Technology*. Harvard University Press.

Goodman, A., Lamping, D. L., & Ploubidis, G. B. (2010). When to use broader internalising and externalising subscales instead of the hypothesised five subscales on the strengths and difficulties questionnaire (sdq): Data from british parents, teachers and children. *Journal of Abnormal Child Psychology*, *38*, 1179–1191.

Goodman, R. (1997). The strengths and difficulties questionnaire: A research note. *Journal of Child Psychology and Psychiatry*, *38*, 581–586.

Goodman, R. (2001). Psychometric properties of the strengths and difficulties questionnaire. *Journal of the American Academy of Child and Adolescent Psychiatry*, *40*, 1337–1345.

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The Review of Economics and Statistics*, *89*(1), 118–133.

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in europe. *American Economic Review*, *99*(2), 58–63.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*, 2509–26.

Grewenig, E. (2022). School track decisions and teacher recommendations: Evidence from german state reforms. *ifo Working Paper*, *353*.

Guvenen, F., Kuruscu, B., Tanaka, S., & Wiczer, D. (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, *12*(1), 210–44.

Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *52*, 271–320.

Heckman, J., & Navarro, S. (2007). Dynamic discrete choice and dynamic treatment effects. *Journal of Econometrics*, *136*, 341–396.

Heckman, J. J. (2008). Schools, skills, and synapses. *Economic Inquiry*, *46*, 289–324.

Heckman, J. J., Humphries, J. E., & Veramendi, G. (2016). Dynamic treatment effects [Innovations in Measurement in Economics and Econometrics]. *Journal of Econometrics*, *191*(2), 276–292.

Heckman, J. J., Humphries, J. E., & Veramendi, G. (2018a). The nonmarket benefits of education and ability. *Journal of human capital*, *12*, 282.

Heckman, J. J., Humphries, J. E., & Veramendi, G. (2018b). Returns to education: The causal effects of education on earnings, health, and smoking. *The journal of political economy*, *126*, S197.

Heckman, J. J., & Raut, L. K. (2016). Intergenerational long-term effects of preschool-structural estimates from a discrete dynamic programming model. *Journal of Econometrics*, *191*(1), 164–175.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behaviour. *Journal of Labor Economics*, *24*.

Hotz, V. J., Xu, L., Tienda, M., & Ahituv, A. (2002). Are there returns to the wages of young men from working while in school? *The Review of Economics and Statistics*, *84*, 221–236.

Humphries, J. E., Joensen, J. S., & Veramendi, G. F. (2019). Complementarities in high school and college investments. *Working Paper*.

Humphries, J. E., & Kosse, F. (2017). On the interpretation of non-cognitive skills – what is being measured and why it matters. *Journal of Economic Behavior & Organization*, *136*, 174–185.

Juhn, C., Murphy, K., Pierce, B., Juhn, C., Murphy, K., & Pierce, B. (1993). Wage inequality and the rise in returns to skill. *Journal of Political Economy*, *101*, 410–42.

Kassenboehmer, S. C., Leung, F., Schurer, S., Kassenboehmer, S. C., Leung, F., & Schurer, S. (2018). University education and non-cognitive skill development. *Oxford Economic Papers*, *70*, 538–562.

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. *Journal of Political Economy*, *105*, 473–522.

Koomen, M., & Backes-Gellner, U. (2022). Occupational tasks and wage inequality in west germany: A decomposition analysis. *Labour Economics*, *79*, 102284.

Levy, F., Murnane, R. J., Karoly, L., Murphy, K., Neumark, D., & O'neill, J. (1992). U.s. earnings levels and earnings inequality: A review of recent trends and proposed explanations. *Source: Journal of Economic Literature*, *30*, 1333–1381.

Lindenlaub, I. (2017). Sorting multidimensional types: Theory and application. *The Review of Economic Studies*, *84*, 718–789.

Lindqvist, E., & Vestman, R. (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the swedish enlistment. *American Economic Journal: Applied Economics*, *3*, 101–28.

Lise, J., & Postel-Vinay, F. (2020). Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, *110*, 2328–76.

Lundberg, S. (2013). The college type: Personality and educational inequality. *Journal of Labor Economics*, *31*, 421–441.

Michaels, G., Natraj, A., & Reenen, J. V. V. (2014). Has ict polarized skill demand? evidence from eleven countries over twenty-five years. *The Review of Economics and Statistics*, *96*, 60–77.

Navarini, L., & Verhaest, D. (2023). Educational attainment, overeducation, and wages: Evidence from a dynamic model. *Working Paper*.

Neyt, B., Verhaest, D., Navarini, L., & Baert, S. (2022). The impact of internship experience on schooling and labour market outcomes. *CESifo Economic Studies*, *68*, 127–154.

OECD. (2013). *Pisa 2012 results: What makes schools successful (volume iv)*.

Rodríguez, J., Urzúa, S., & Reyes, L. (2016). Heterogeneous economic returns to post-secondary degrees: Evidence from chile. *Journal of Human Resources*, *51*, 416–460.

Rohrbach-Schmidt, D., & Tiemann, M. (2013). Changes in workplace tasks in germany - evaluating skill and task measures. *Journal for Labour Market Research*, *46*(3), 215–237.

Rutter, M. (2006). The promotion of resilience in the face of adversity. *Families Count: Effects on Child and Adolescent Development*, 26–52.

Schurer, S. (2017). Bouncing back from health shocks: Locus of control and labor supply. *Journal of Economic Behavior and Organization*, *133*, 1–20.

Sorrenti, G., Zölitz, U., Ribeaud, D., & Eisner, M. (2020). *The causal impact of socio-emotional skills training on educational success* (CESifo Working Paper Series No. 8197). CESifo.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, *24*(2), 235–270.

Tinbergen, J. (1974). Substituion of graduate by other labour. *Kyklos*, *27*, 217–226.

Tinbergen, J. (1975). *Income differences: Recent research*. North-Holland Publishing Company, Amsterdam.

Todd, P. E., & Zhang, W. (2020). A dynamic model of personality, schooling, and occupational choice. *Quantitative Economics*, *11*, 231–275.

Toppeta, A. (2022). Skill formation with siblings. *Working Paper*.

Wagner, G. G., Frick, J. R., & Schupp, J. (2007). Scope, evolution and enhancements. *SOEPpapers on Multidisciplinary Panel Data Research*.

Weinberger, C. J. (2014). The increasing complementarity between cognitive and social skills. *The Review of Economics and Statistics*, *96*(5), 849–861.

Willis, R., Rosen, S., Willis, R., & Rosen, S. (1979). Education and self-selection. *Journal of Political Economy*, *87*, S7–36.

A Data Appendix

I use data from ESCO and the GSOEP, including the complete panel data set from 1984 to 2020. In this section of the Appendix, I carefully describe the datasets and the resulting data used in my analysis.

A.1 ESCO Appendix

I investigate changes in the task content of occupations by linking the ESCO dictionary for each occupation to the GSOEP Dataset. The ESCO[12] serves as a comprehensive multilingual classification system for labour markets in Europe[13]. It is a dictionary that outlines, identifies, and categorizes professional occupations and relevant skills crucial for the European Union's labor market, education, and training sectors. It is a project of the European Commission used to harmonize labour markets in the EU. ESCO encompasses a collection of 3'008 occupation descriptions and 13'890 skills associated with these occupations, all of which have been translated into 28 languages. I use the entire dataset of ESCO and link skill groups to each occupation, such as they may either be essential or optional for each occupation (ISCO-08 4 digits). Each occupation is classified using a set of 101 broader skill groups, containing all 13'890 narrower skills. These skill requirement descriptions are broad and include many different narrower skills. As an example, each occupation may have skill requirements in "assembling and fabricating products", or "recruiting and hiring", as well as "operating mobile plant", or, also, "leading others". For instance, the latter skill group "leading others", described as *guide, direct and motivate others*, comprises narrower skills, such as "build team spirit", "delegate responsibilities", "lead others" and "motivate others". These skills can be further decomposed into narrower skills, such as "lead others", described as *guide and direct others towards a common goal, often in a group or team*, comprises a large set of narrower skills, such as "coordinate construction activities", or " manage production systems", or "supervise dental technician staff".[14] These narrower skills are considered either essential or optional for each occupation. Therefore, the narrow skill "coordinate construction activities" is essential for occupations, such as underwater construction supervisor, demolition super-

[12]See more details on the website of ESCO.

[13]ESCO: The ESCO-O*NET crosswalk represents a first successful attempt to connect two international standards by combining the use of artificial intelligence (AI) techniques with human validation.

[14]It is possible to recover the full list at this link.

visor, or bridge construction supervisor. I categorize each occupation using the full set of around 13'890 skills descriptions in the following way. For each occupation, I use the 2 digits (broader) skill groups and I define each occupation with a binary outcome if the occupation includes any of the narrower skill requirements included in a given (broader) skill group. Moreover, I also use the groups for the transversal skills and competences. In this way, I have a set of binary outcomes for each occupation, including complete information for each set of skill requirements. While having reduced greatly the number of skills requirements, going from around 13'000 detailed skill requirements to around 100 broader skill groups[15], I need to further reduce this dimensionality.

A.1.1 Measurement System for Tasks

In this section, I further reduce the dimensionality of ESCO, in order to obtain a limited amount of variables to describe the task content of occupation in Germany. The first step is to perform a Principal Component Analysis using 98 different broader groups selected from ESCO. From Figure 12, it is clear that 3 main components are explaining a large part of the variation, while from the 4th component, the added value is only marginal.

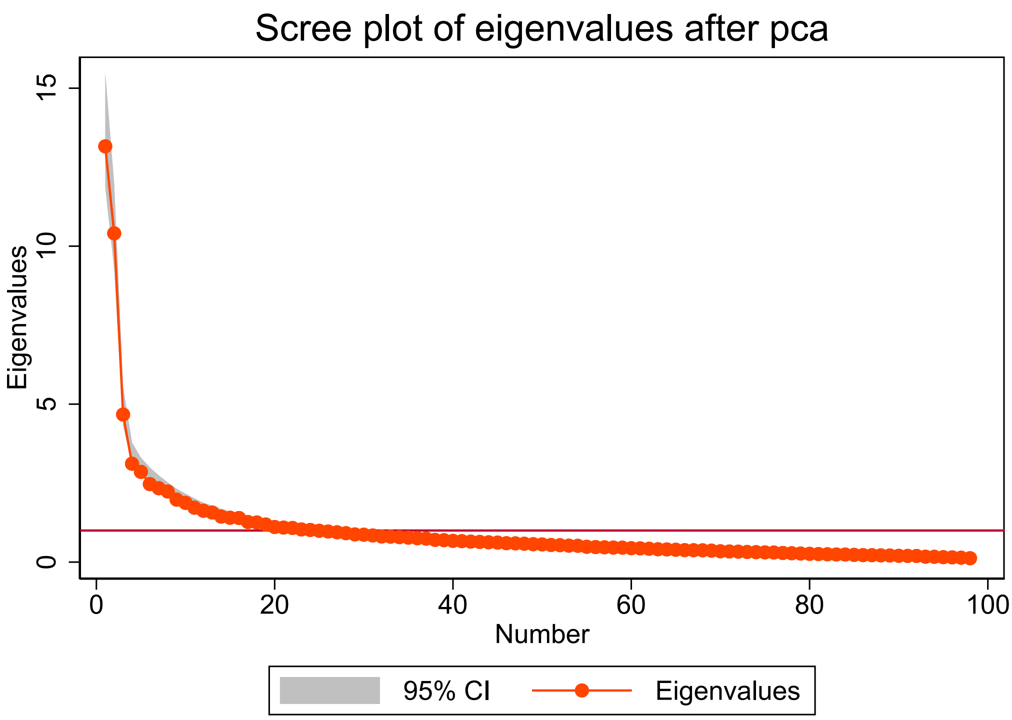


Figure 12: ESCO PCA Analysis

[15]It is possible to find the complete list of broader skill groups at this link.

The second step consists of both an Explanatory and a Confirmatory Factor Analysis (EFA and CFA). Starting with EFA, from Figure 13, the results are rather similar to the PCA, as shown in Figure 12, with three factors capturing a large part of the variation, and with only marginal value to further factors.

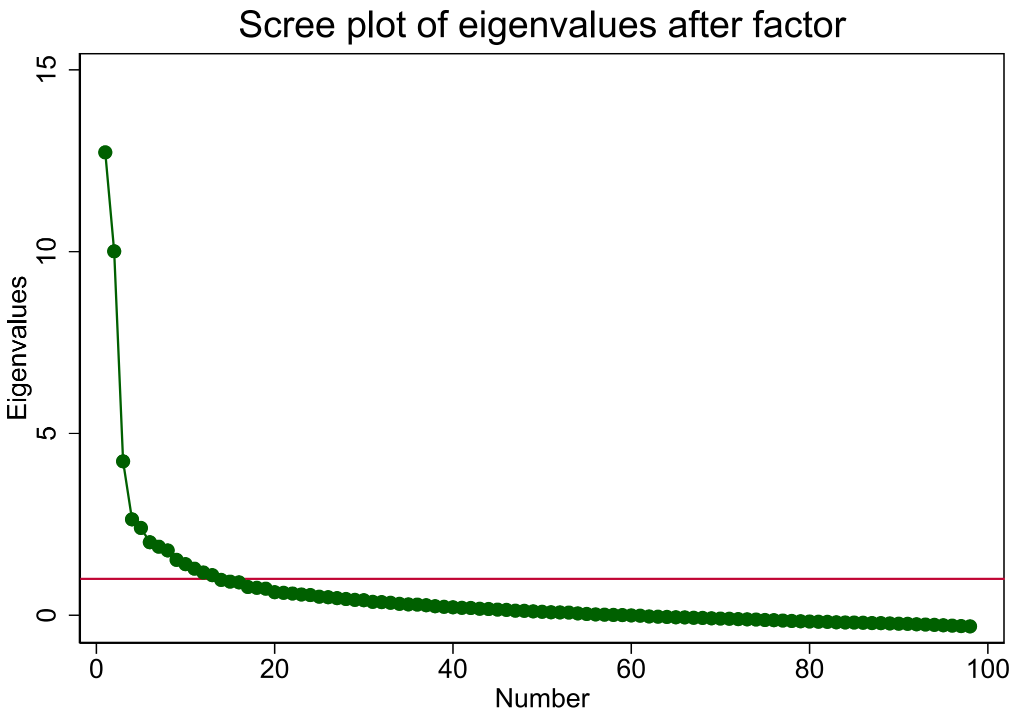


Figure 13: ESCO EFA Analysis

In Table 14, I show that the three main components extracted using PCA are highly correlated with the three main factors extracted using EFA.

Table 14: Correlation: PCA and EFA

	PCA Component 1	PCA Component 2	PCA Component 3
Factor 1	0.8672	0.1008	-0.4867
Factor 2	-0.0448	0.9912	0.1199
Factor 3	0.5187	-0.0868	0.8491

Of course, PCA and EFA are related, but there are important differences, for instance, regarding the measurement error. At this point, I use CFA to extract a series of three factors, based on the literature on the task-based approach, identifying three main tasks: routine, non-routine analytical (cognitive), and social (Deming, 2017). The main point is that these skill requirements all measure an underlying factor that ranks occupations based on their skill requirements. This measure is used to create a bundle of skill requirements or task content by occupation, that measures the different skill requirements. To identify the model, I use a set of dedicated measures for each factor and normalize the parameter to 1. I include both ESCO Skills and ESCO Transversal Skills and Competences. The model for the CFA is summarized in Table 15.

Measures		Social	Routine	Cognitive
ESCO Skills				
handling and disposing of waste and hazardous materials	*b*	x	x	x
moving and lifting	*b*	x	x	x
making moulds, casts, models and patterns	*b*	x	x	x
positioning materials, tools or equipment	*b*	x	x	x
tending plants and crops	*b*	x	x	x
transforming and blending materials	*b*	x	x	x
washing and maintaining textiles and clothing	*b*	x	x	x
cleaning	*b*	x	x	x
assembling and fabricating products	*b*	x	x	x
using hand tools	*b*	x	x	x
handling animals	*b*	x	x	x
sorting and packaging goods and materials	*b*	x	x	x
handling and moving	*b*	x	x	x
monitoring developments in area of expertise	*b*	x	x	x
monitoring, inspecting and testing	*b*	x	x	x
documenting and recording information	*b*	x	x	x
analysing and evaluating information and data	*b*	x	x	x
processing information	*b*	x	x	x
information skills	*b*	x	x	x
measuring physical properties	*b*	x	x	x
conducting studies, investigations and examinations	*b*	x	x	x
managing information	*b*	x	x	x
calculating and estimating	*b*			x
accessing and analysing digital data	*b*	x	x	x
setting up and protecting computer systems	*b*	x	x	x
using digital tools to control machinery	*b*	x	x	x
using digital tools for collaboration, content creation and problem solving	*b*	x	x	x
programming computer systems	*b*	x	x	x
working with computers	*b*	x	x	x
building and repairing structures	*b*	x	x	x
constructing	*b*	x	x	x
installing interior or exterior infrastructure	*b*	x	x	x
finishing interior or exterior of structures	*b*	x	x	x
building and developing teams	*b*	x	x	x
organising, planning and scheduling work and activities	*b*	x	x	x
developing objectives and strategies	*b*	x	x	x
recruiting and hiring	*b*	x	x	x
supervising people	*b*	x	x	x
allocating and controlling resources	*b*	x	x	x
making decisions	*b*	x	x	x
management skills	*b*	x	x	x
leading and motivating	*b*	x	x	x
performing administrative activities	*b*	x	x	x
installing, maintaining and repairing mechanical equipment	*b*	x	x	x
operating machinery for the extraction and processing of raw materials	*b*	x	x	x
operating machinery for the manufacture of products	*b*	x	x	x
using precision instrumentation and equipment	*b*	x	x	x
driving vehicles	*b*	x	x	x
installing, maintaining and repairing electrical, electronic and precision equip	*b*	x	x	x
operating watercraft	*b*	x	x	x
working with machinery and specialised equipment	*b*	x	x	x

operating aircraft	b	x	x	x
operating mobile plant	b	x	x	x
protecting and enforcing	b	x	x	x
assisting and caring	b	x	x	x
counselling	b	x	x	x
providing health care or medical treatments	b	x	x	x
preparing and serving food and drinks	b	x	x	x
providing information and support to the public and clients	b	x	x	x
providing general personal care	b	x	x	x
designing systems and products	b	x	x	x
advising and consulting	b	x	x	x
writing and composing	b	x	x	x
negotiating	b	x	x	x
presenting information	b	x	x	x
working with others	b	x	x	x
teaching and training	b	x	x	x
obtaining information verbally	b	x	x	x
communication, collaboration and creativity	b	x	x	x
using more than one language	b	x	x	x
performing and entertaining	b	x	x	x
liaising and networking	b	x	x	x
promoting, selling and purchasing	b	x	x	x
solving problems	b	x	x	x
creating artistic, visual or instructive materials	b	x	x	x
ESCO Transversal Skills and Competences				
working with numbers and measures	b	x	x	x
working with digital devices and applications	b	x	x	x
processing information, ideas and concepts	b	x	x	x
planning and organising	b	x	x	x
dealing with problems	b	x	x	x
thinking creatively and innovatively	b	x	x	x
working efficiently	b	x	x	x
taking a proactive approach	b	x	x	x
maintaining a positive attitude	b	x	x	x
demonstrating willingness to learn	b	x	x	x
communicating	b	x	x	x
supporting others	b	x		
collaborating in teams and networks	b	x	x	x
leading others	b	x	x	x
following ethical code of conduct	b	x	x	x
manipulating and controlling objects and equipment	b		x	
responding to physical circumstances	b	x	x	x
applying health-related skills and competences	b	x	x	x
applying environmental skills and competences	b	x	x	x
applying civic skills and competences	b	x	x	x
applying cultural skills and competences	b	x	x	x
applying entrepreneurial and financial skills and competences	b	x	x	x
applying general knowledge	b	x	x	x
promoting, selling and purchasing	b	x	x	x
solving problems	b	x	x	x
creating artistic, visual or instructive materials	b	x	x	x

Table 15: Measurement system for latent factors for task content

This is done in order to classify each occupation based on a set of task content using ESCO. For identifying γ^e, I use a set of $m^E \in M^E$ measurements, for $e \in \{S, R, C\}$, where S is for social tasks, R for routine tasks and C for non-routine analytical (cognitive):

$$m_{ij}^E = a_j + \lambda_{ji}\gamma_i^S + \lambda_{ji}\gamma_i^R + \lambda_{ji}\gamma_i^C + \varepsilon_{ij}, \tag{14}$$

where $m^E \in M^E$ is a set of binary outcomes for each skill group. Indeed, m^E identifies if for a given occupation, one of the narrower skills of the broader skill group is cited by the ESCO dictionary as either essential or optional. The three factors obtained are interpreted as social, routine, and cognitive task content for each occupation.

Table 16: Correlation: PCA, EFA and CFA

	PCA Component 1	PCA Component 2	PCA Component 3	Factor 1	Factor 2	Factor 3	Social γ^S	Routine γ^R	Cognitive γ^C
Social γ^S	0.9618	0.0172	0.2403	0.7186	0.0029	0.7023	1		
Routine γ^R	0.0635	0.9494	-0.1906	0.2436	0.9147	-0.2118	0.0309	1	
Cognitive γ^C	0.7935	0.4413	-0.3864	0.9207	0.3556	0.0446	0.6834	0.572	1

In Table 16, I show the correlation between measures extracted by PCA, EFA, and CFA. Essentially, factors interpreted as social is highly correlated with PCA component 1 and with Factor 1, while routine is highly correlated with PCA component 2 and with Factor 2. Regarding, the non-routine analytical (cognitive) factor, it is actually strongly correlated between PCA component 1 and Factor 1, indicating a strong correlation between social and cognitive tasks (as indicated in Deming, 2017).

A.1.2 Alternative Measures for Robustness Checks

As a robustness check, I can classify occupations using a different measure of task content. Other than using PCA or EFA measures for defining occupations, I could use a continuous measure, without relying on factors.

Table 17: Broader Groups and Task Content

Social	**Routine**	**Nonroutine Analytical (Cognitive)**
S1 - communication, collaboration and creativity	S6 - handling and moving	S2 - information skills
S3 - assisting and caring	S7 - constructing	S5 - working with computers
S4 - management skills	S8 - working with machinery and specialised equipment	
T4 - social and communication skills and competences		T1 - core skills and competences
	T5 - physical and manual skills and competences	T2 - thinking skills and competences
		T3 - self-management skills and competences
		T6 - life skills and competences

In Table 17, I use a set of specific broader groups to define a continuous measure of task content, which is based on the number of skill requirements required by each occupation for each of these three set of broader groups.

Table 18: Correlation: Factors and Continous Measures

	Social γ^S	Routine γ^R	Cognitive γ^C	Social cont.	Routine cont.	Cognitive cont.
Social cont.	0.9727	0.0142	0.6725	1		
Routine cont.	0.0038	0.903	0.3396	-0.0189	1	
Cognitive cont.	0.8219	0.3099	0.8856	0.7749	0.1411	1

Notes: Social γ^S, Routine γ^R, and Cognitive γ^C denotes the factors extracted using the model, while Social cont., Routine cont., and Cognitive cont. denotes the continuous measures of task content, normalizing the number of narrower skills contained in each occupation.

In Table 18, I show the correlation between factors and continuous measures. Essentially, continuous measures are highly correlated with their respective factors. Again, social and cognitive task measures are highly correlated.

A.2 GSOEP Appendix

I investigate the changes in wage returns to multidimensional skills using data from Germany. The analysis uses data from the German Socio-Economic Panel data (GSOEP, 2020), which is a longitudinal micro-dataset containing a large number of individuals and households in Germany, and was started in 1984. Presently, the GSOEP includes data on over 20,000 individuals and 10,000 households (see Wagner et al., 2007; Humphries and Kosse, 2017). This dataset is representative and provides a comprehensive range of socio-economic information on individuals and private households in Germany.

The initial data collection began in 1984, with about 12,200 adult respondents randomly selected from West Germany. Following the German reunification in 1990, the GSOEP was expanded to include approximately 4,500 individuals from East Germany, and later, additional samples were added for further supplementation. Beginning in 2000 (for individuals born in 1983), a Youth questionnaire was administered to all young people at the age of 17, which contains specific questions about education and aspirations as they are being interviewed for the first time. From 2006 (for those born in 1989), the questionnaire included a comprehensive set of measures, assessing both cognitive and non-cognitive abilities.[16]

[16]To investigate the cognitive performance potential of adolescents, they developed a questionnaire based on the I-S-T 2000 test, which is suitable for an individual panel survey.

The GSOEP's Youth Questionnaire contains data on 9,370 individuals, which can be complemented with subsequent individual questionnaires. Overall, I have 125,728 individual-year observations for these individuals, which includes data from the household questionnaire (59,188 individual-year observations after the age of 17 and subsequent to the receipt of the Youth questionnaire) and data from the individual surveys conducted after the age of 17. Of the 9,370 individuals, data on potential cognitive performance is available for 4,055 individuals. Thus, I restrict our sample for estimating the model to those individuals for whom I have cognitive test data, resulting in a final sample of 4,055 individuals.

A.2.1 Demographic Cohorts

Potentially, I would estimate the models with time-specific estimates. However, to keep the model tractable and estimate the changes across cohorts, I define two different demographic cohorts: M, those born before 1995 (Millennials, following a definition of demographic cohorts), and Z, those born after 1995 (also known as Generation Z). The main difference between these two demographic cohorts is the different use of ICTs, as explained by PEW research.[17]

From a practical perspective, in Table 19, I show that the year of birth 1995 divides the Youth questionnaire in half, with a cumulative percentage of 52,69% of individuals born before or in 1995.

Table 19: Year of Birth: Youth Questionnaire

Year of Birth	Freq.	Percent	Cum.
...	...	...	...
1993	404	4.31	41.31
1994	531	5.67	46.98
1995	535	5.71	52.69
1996	568	6.06	58.75
1997	578	6.17	64.92
...	...	...	...
Total	9,368	100	

However, as a further robustness check, I also estimate the models removing individuals at the margins of 1995 (including individuals born in 1994 and 1996).

[17] See, for instance, Generation Z report by PEW research institute.

A.2.2 Measurement System for Skills

Using the GSOEP Dataset, I have access to a large set of measures of cognitive and non-cognitive skills. Potentially, it is possible to utilize this extensive list of measures and estimate each individual effect separately. However, it is important to consider that these skill measures are likely to be correlated with one another. Additionally, it is crucial to prioritize parsimony when dealing with such a vast amount of information in measurement. These measures are likely to be measures of underlying common factors.

Therefore, I link the questionnaire on cognitive tests (COGDJ) to the youth questionnaire (JUGENDL).[18] COGDJ includes a set of three different standardized tests, each containing 20 questions. The JUGENDL Questionnaire comprises an extensive range of inquiries, encompassing personal characteristics, time allocation, aspirations, and various other traits. Lastly, this questionnaire also includes school grades and other details about the schooling skill of each individual.[19] Indeed, both contain a large set of measurements aimed at identifying, with measurement error, a limited number of latent factors. Following Deming (2017), Humphries et al. (2019), and Toppeta (2022), I focus on identifying a latent factor for cognitive skills (θ^c), while identifying two latent factors from non-cognitive measurements: in Toppeta (2022), these are referred to as externalizing and internalizing factors. Indeed, The psychometric literature identifies two dimensions of socio-emotional development: internalizing (ability to focus their drive and determination) and externalizing (ability to engage in interpersonal activities) skills (Achenbach, 1966; Goodman, 1997, 2001; Goodman et al., 2010; Achenbach et al., 2016). In line with the literature on returns to skills, following Deming (2017), I refer to them simply as a social skill (θ^{sc}) and a more general non-cognitive skill (θ^{nc}). This latter skill, therefore, is more related to diligence, the ability to focus, to be hard-working, and to work efficiently, without wasting time.

As done with ESCO, I start by analyzing the non-cognitive skills measure using a PCA and a EFA.

In Figure 14, there are at least, 4 components that explain a significant fraction of the variation in non-cognitive measures.

[18]To measure cognitive skills, the participants took part in a validated short version of the well-established "I-S-T 2000 R"(Amthauer et al., 2001), covering all three subsets which are verbal, numerical, and figural abilities (for details see Solga et al., 2005)

[19]i.e. if the individual enroled in advanced or basic courses in German, Mathematics or Foreign Languages.

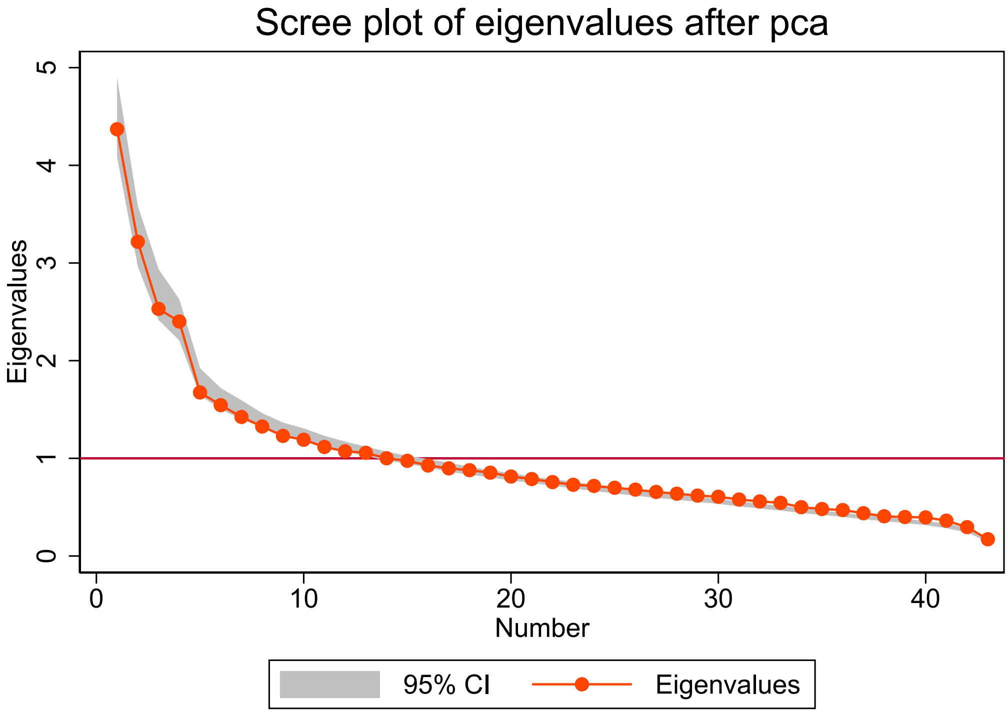


Figure 14: GSOEP PCA Analysis

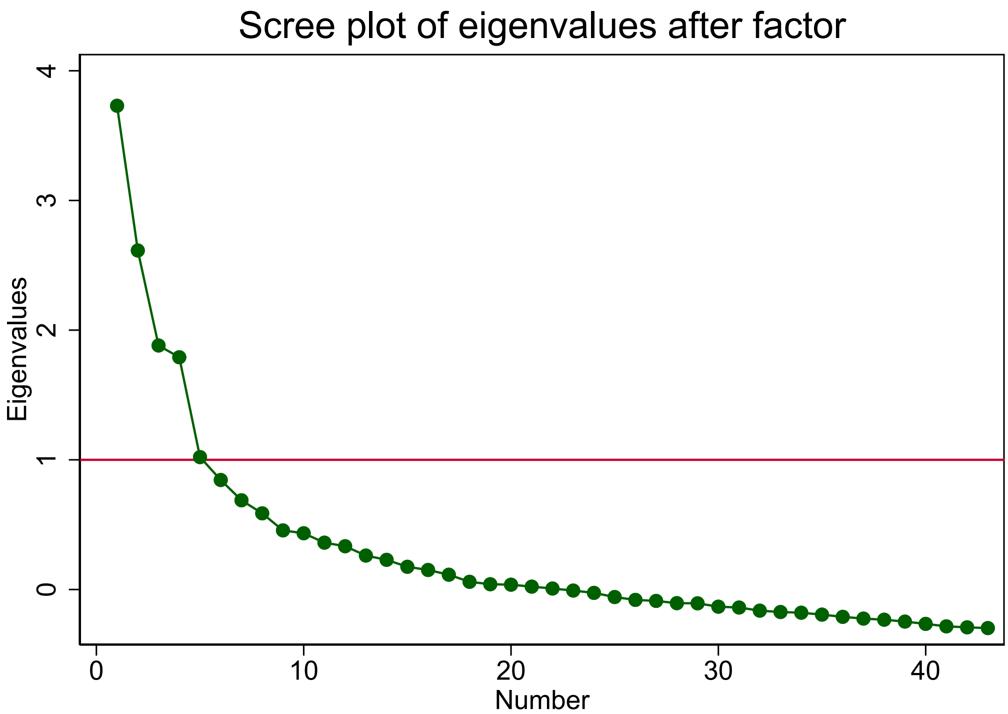


Figure 15: GSOEP EFA Analysis

This is also confirmed in Figure 15, where 4 main factors are above the mean.

I use a measurement system with both categorical and continuous variables to measure the latent factors. The measurement system with categorical items exploits the variation from each item - instead of aggregating their responses in continuous subscales to estimate a factor model with continuous items.[20] As in Humphries and Kosse (2017), I estimate non-cognitive skills from a large set of measurements available in the GSOEP dataset: participation in extracurricular activities (including competition in sports), time allocation to a set of activities, satisfaction with school achievements, self-reported probability of future success, risk preference, time preference, trust measures, personal characteristics (Big 5), political interest, locus of control and amount of closed friends. The full list is included in Table 20. In comparison to Humphries et al. (2019), I interpret these factors as skills rather than abilities. This interpretation is based on the fact that these measures were obtained at the age of 17, suggesting a developmental aspect influenced by external factors, rather than being solely innate or predetermined abilities. Moreover, I do not include exogenous and schooling-specific characteristics. In this paper, skills are defined as endogenous, meaning they can be acquired and improved through learning and practice, while abilities are considered inherent or exogenous traits. In my analysis employing a dynamic treatment effect approach, I incorporate the notion of ability through the utilization of finite mixtures and an exogenous number of unobserved types. These unobserved types are assumed to possess distinct developmental traits and employ a set of skills in different ways (refer to the Section 3 for more details).[21]

Using a large set of cognitive standardized tests, academic performances, and non-cognitive measures, I identify three latent factors: θ^c, θ^{nc} and θ^{sc}. These factors are underlying skills, measured with an error by the GSOEP dataset questionnaires and they are related to, respectively: cognitive, non-cognitive, and social skills. As mentioned before, I utilize a set of measurements for identifying θ^c, while I identify the two measurements θ^{nc} and θ^{sc} using the same set of measurements and, therefore, these are two ability identified using the same measurement system. In this case, non-cognitive skills

[20]Cunha et al. (2010), Agostinelli et al. (2020), Attanasio, Blundell, et al. (2020), and Attanasio, Cattan, et al. (2020) employ a measurement approach that utilizes continuous items and focuses on a limited number of human capital dimensions. Specifically, they examine a single aspect of socio-emotional development, rather than considering the two distinct dimensions of socio-emotional skills, namely internalizing and externalizing.

[21]e.g. Individuals may differ in the productivity of having both high measures of cognitive and non-cognitive.

are conditional on social skills.

The set of measurements is consistently large for each of these measures. I use a non-linear factor model to identify these factors using a comprehensive and large set of measures. For identifying θ^c, I use a set of $m^c \in M^c$ dedicated measurements:

$$m_{ij}^c = a_j + \lambda_{ji}\theta_i^c + \varepsilon_{ij} \tag{15}$$

Regarding non-cognitive skills, I identify 2 factors from a set of measurements $m^{nc} \in M^{nc}$:

$$m_{ij}^{nc} = a_j + \lambda_{ji}^1\theta_i^{nc1} + \lambda_{ji}^2\theta_i^{nc2} + \varepsilon_{ij} \tag{16}$$

Based on this estimation, I interpret θ^{nc1} as a general measure of non-cognitive abilities, θ^{nc}, such as grit, hard-working, conscientiousness, patient, while I interpret θ^{nc2} as θ^{sc}, as a measure of non-cognitive skills linked to sociability, extroversion, leadership and other skills linked to higher interactions. Of course, individuals may have high skills in both of these factors. This could be referred to as an externalizing and an internalizing factor (Toppeta, 2022).

Table 20 contains the full measurement system for the latent factors. It consists of 75 measures for the cognitive factor θ^c, and of 76 measures for extracting two non-cognitive factors θ^{nc} and θ^{sc}.[22] I include a set of parental involvement measures for identifying the cognitive factor because of two main reasons: (i) an individual may display a larger cognitive skill and, therefore, parents may be more willing to help him develop her skills and (ii) more involved parents may be a proxy for early schooling investments with high returns on cognitive skills at the age of 17.

Table 20: Measurement system for latent factors θ^c, θ^{nc} and θ^{sc}

Measures		θ^c	θ^{nc}	θ^{sc}
Data on cognitive tests (COGDJ)				
20 Analogies questions	*b*	x		

[22]Measures highlighted in italics are chosen to be reference measures for identifying the latent factors. Respectively: Grade Mathematics for θ^c, personal characteristics: work carefully for θ^{nc} and personal characteristics: communicative for θ^{sc}. The normalization of the factor loadings to 1 and choosing dedicated measures are crucial for identifying these factors.

20 Arithemtic Operator questions	*b*	x		
20 Figures questions	*b*	x		
Youth Questionnaire (JUGENDL)				
Grade German	*c*	x		
Grade Mathematics	*c*	x		
Grade 1. Foreign Langauge	*c*	x		
Advanced Course German	*b*	x		
Advanced Course Mathematics	*b*	x		
Advanced Course 1. Foreign Langauge	*b*	x		
Support tutor	*b*	x		
Abitur preferred certificate	*b*	x		
Parents Show Interest In Performance	*b*	x		
Parents Help With Studying	*b*	x		
Disagreements With Parents Over Studies	*b*	x		
Parents Take Part In Parents-Evening	*b*	x		
Parents Come To Teacher Office Hours	*b*	x		
Parents Visit Teacher Outside Office Hrs.	*b*	x		
Involved As Parents Representative	*b*	x		
Class Representative	*b*		x	x
Student Body President	*b*		x	x
Involved With School Newspaper	*b*		x	x
Belong To Theatre, Dance Group	*b*		x	x
Belong To Choir, Orchestra, Music Group	*b*		x	x
Belong To Volunteer Sport Group	*b*		x	x
Other Kind Of School Group	*b*		x	x
Musical Lessons Outside Of School	*b*		x	x
Musically Active	*b*		x	x
Sport Activity	*b*		x	x
Take Part In Competitions In This Sport	*b*		x	x
How Often Listen To Music	*c*		x	x
How Often Play Music Or Sing	*c*		x	x
How Often Do Sports	*c*		x	x
How Often Dance Or Act	*c*		x	x
How Often Do Tech. Activities	*c*		x	x
How Often Read	*c*		x	x
How Often Spend Time Steady Boy-,Girlfriend	*c*		x	x
How Often Spend Time Best Friend	*c*		x	x

How Often Spend Time Clique	*c*	x	x
How Often Youth Centre, Community Centre	*c*	x	x
How Often Do Volunteer Work	*c*	x	x
Frequency of time in church, attending religious events	*c*	x	x
Satisfaction With Overall School Grades	*c*	x	x
Satisfaction With German Grades	*c*	x	x
Satisfaction With Mathematics Grades	*c*	x	x
Satisfaction With Main Foreign Langauge	*c*	x	x
Probability in %: favoured apprenticeship or university place	*c*	x	x
Probability in %: apprenticeship or university place	*c*	x	x
Probability in %: workplace	*c*	x	x
Probability in %: job success	*c*	x	x
Probability in %: unemployed	*c*	x	x
Probability in %: limitation family	*c*	x	x
Probability in %: self employed	*c*	x	x
Probability in %: job abroad	*c*	x	x
Probability in %: marriage	*c*	x	x
Probability in %: partnership	*c*	x	x
Probability in %: one child	*c*	x	x
Probability in %: more than one child	*c*	x	x
Willingness to take risks	*c*	x	x
Trust People	*c*	x	x
Cannot rely on people	*c*	x	x
Distrust Strangers	*c*	x	x
Have fun today, not think about tomorrow	*c*	x	x
Big 5 Personality traits		x	x
Personal characteristics: work carefully	*c*	x	
Personal characteristics: communicative	*c*		x
Personal characteristics: abrasive towards others	*c*	x	x
Personal characteristics: introduce new ideas	*c*	x	x
Personal characteristics: often worry	*c*	x	x
Personal characteristics: can forgive others	*c*	x	x
Personal characteristics: am lazy	*c*	x	x
Personal characteristics: am outgoing/sociable	*c*	x	x
Personal characteristics: importance of esthetics	*c*	x	x
Personal characteristics: am nervous	*c*	x	x
Personal characteristics: carryout duties efficiently	*c*	x	x
Personal characteristics: reserved	*c*	x	x

Personal characteristics: considerate, friendly	*c*	x	x
Personal characteristics: lively imagination	*c*	x	x
Personal characteristics: be relaxed, no stress	*c*	x	x
Personal characteristics: hunger for knowledge, curious	*c*	x	x
		x	x
Frequency of Being Angry in the Last 4 Weeks	*c*	x	x
Frequency of Being Worried in the Last 4 Weeks	*c*	x	x
Frequency of Being Happy in the Last 4 Weeks	*c*	x	x
Frequency of Being Sad in the Last 4 Weeks	*c*	x	x
Political Interests		x	x
Locus of control		x	x
How my life goes depends on me	*c*	x	x
Compared to other people, I have not achieved what I deserve	*c*	x	x
What a person achieves in life is above all a question of fate or luck	*c*	x	x
I frequently have the experience that other people have a controlling influence over my life	*c*	x	x
You have to work hard to succeed	*c*	x	x
When I run up against difficulties in life, I often doubt my own abilities	*c*	x	x
The opportunities that I have in life are determined by social conditions	*c*	x	x
Innate abilities are more important than any efforts one can make	*c*	x	x
I have little control over the things that happen in my life	*c*	x	x
If a person is socially or politically active, he/she can have an effect on social conditions	*c*	x	x
Amount Of Closed Friends	*c*	x	x

The latent factors are measures of the following skills, selecting the personal characteristics survey questions, used for extracting the Big 5.[23]

In Table 22, I show the correlation between the measures of non-cognitive and social

[23]Note that I refer to skills as these are measures at the age of 17 and they are endogenously determined by the human capital formation process.

Table 21: Interpretation of Latent Factors

Big 5 questions:	θ^c	θ^{nc}	θ^{sc}
Personal characteristics: work carefully	-0.003	**0.742**	0.192
Personal characteristics: communicative	-0.031	0.223	**0.814**
Personal characteristics: abrasive towards others	-0.043	-0.307	0.139
Personal characteristics: introduce new ideas	0.004	0.268	0.563
Personal characteristics: often worry	-0.037	-0.011	0.044
Personal characteristics: can forgive others	0.056	0.274	0.233
Personal characteristics: am lazy	0.083	**-0.526**	**-0.028**
Personal characteristics: am outgoing/sociable	-0.004	**0.158**	**0.843**
Personal characteristics: importance of esthetics	0.097	0.200	0.252
Personal characteristics: am nervous	-0.021	-0.128	-0.243
Personal characteristics: carryout duties efficiently	0.092	**0.759**	**0.284**
Personal characteristics: reserved	0.018	**0.061**	**-0.598**
Personal characteristics: considerate, friendly	-0.026	0.506	0.253
Personal characteristics: lively imagination	0.062	0.110	0.312
Personal characteristics: be relaxed, no stress	0.046	0.321	0.292
Personal characteristics: hunger for knowledge, curious	0.205	0.453	0.278

skills with the PCA and EFA measures.

Table 22: Correlation: PCA, EFA and CFA

	PCA Comp. 1	PCA Comp. 2	PCA Comp. 3	PCA Comp. 4	Factor 1	Factor 2	Factor 3	Factor 4
Non-cognitive skills θ^{nc}	0.7425	0.117	-0.6063	0.1928	-0.3365	0.1233	0.1769	0.9278
Social skills θ^{sc}	0.7939	0.2586	0.4881	0.0976	-0.1801	0.9437	0.2263	0.2

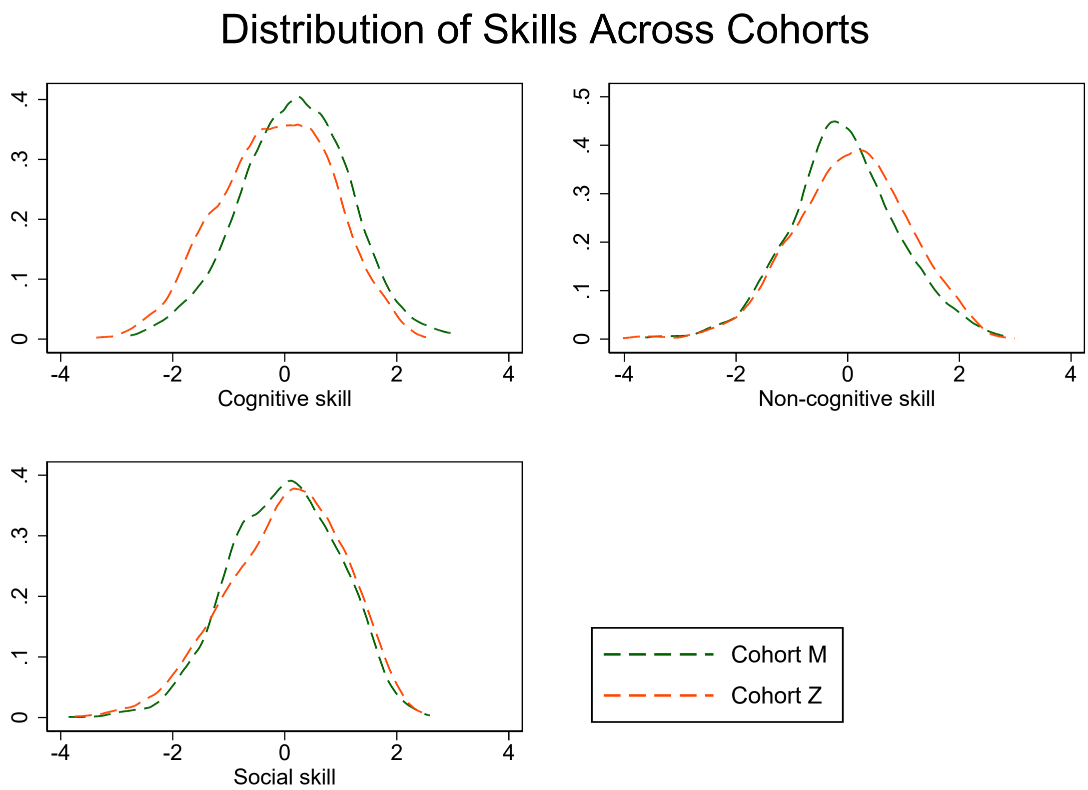
Essentially, my latent factors are strongly correlated with factor 2 and factor 4, respectively. Regarding PCA, it seems they essentially capture component 3.

In the first step, I identify each of these 3 models, while, in the second step, I include these latent skills into a dynamic model of human capital accumulation, considering them as endogenous to prior educational choices. Table 23 presents the correlations between the measures. It shows that social and non-cognitive skills exhibit a correlation of 0.35, whereas cognitive skills have a correlation of 0.05 with social skills and 0.13 with non-cognitive skills.

Table 23: Correlation across skill factors

	θ^c	θ^{nc}	θ^{sc}
θ^c	1		
θ^{nc}	0.1331	1	
θ^{sc}	0.0535	0.3505	1

Figure 16: Distribution of skills across cohorts



B Model

B.1 Expectation-Maximization Algorithm

In this setting, I estimate the model using the EM algorithm. If we knew the probability types, the likelihood of the model would be completely separable and we could estimate the entire model in stages. However, since these are unobserved to the econometrician, the estimation of this model is done by using an Expectation-Maximization (EM) algorithm (Arcidiacono and Jones, 2003). This method was originally developed by Dempster et al. (1977), and applied to DDC models by, amongst others, Arcidiacono (2004), Arcidiacono and Ellickson (2011), and Arcidiacono and Miller (2011). This method is composed of (i) an expectation and (ii) a maximization step. These two steps are repeated until convergence is achieved.

In the expectation step, we compute the probability of each individual being in each heterogeneity type k, based on the likelihood value for each $k \in K$: $\mathcal{L}_i$. Indeed, for each type k, we know the type-specific likelihood and the total expected likelihood weighted by the probability of being in each type k, $\pi_{k,i}$:

$$\mathcal{L}_i = \sum_{i=1}^{I} \left[\sum_{k=1}^{K} \pi_k \log \left(\prod_{t=1}^{T} \ell_{it}(\gamma_k) \right) \right], \tag{17}$$

Bayes' rule implies that the probability for individual i of being a type k, conditional on the observed variables, endogenous outcomes and unobservables, is:

$$\hat{p}_{mi} = \frac{\pi_{mi}\mathcal{L}_i}{\sum_{m=1}^{M} \pi_{mi}\mathcal{L}_i} \tag{18}$$

In the maximization step, the conditional probabilities of being heterogeneity type m are treated as given, which allows us to optimize the full model by maximum likelihood. Note that, as Arcidiacono and Jones (2003) show, the maximization step can be now carried out in stages: indeed, once we treat the heterogeneity probabilities as given, the likelihood is again fully separable, as mentioned at the beginning of this section.

$$\mathcal{L}_i = \sum_{i=1}^{I} \left[\sum_{m=1}^{M} \hat{p}_{mi} \log \left(\prod_{t=1}^{T} \ell_{it}(\gamma_m) \right) \right], \tag{19}$$

After the maximization step, we update the conditional probabilities and iterate to the next maximization. This process is repeated until convergence is obtained. To identify the optimal number of heterogeneity types m, we re-estimate the model by gradually adding up to four types to the model. Moreover, as the model does not have a global solution, we need to re-estimate the model multiple times and select the best-fitting model.

B.2 Model Selection

In Table 24, I include the log-likelihood for each model by cohort and number of unobserved types, using different starting values.

Based on these values, I select the model with 3 heterogeneity types in both cohorts for two main reasons: (i) to keep consistency across cohorts and (ii) as for cohort Z, the model with 4 heterogeneity types does not converge correctly.

Table 24: Model Selection

Cohort:	Number of heterogeneity types:	Seed (random starting values) 1	2	3	4	5
	2	16483.474	16554.381	16554.646	16555.323	16554.629
M	3	16114.014	**16075.457**	16075.469	16075.467	16075.475
	4	15755.739	15897.254	15697.410	15747.197	15754.570
	2	14416.782	14449.712	14449.773	14449.781	14449.855
Z	3	14838.979	14687.862	**14805.691**	14687.853	14838.975
	4	15085.964	15207.404	15086.003	15086.002	15207.405

B.3 Treatment Effects

I begin with representing log-hourly starting wages $\log(\text{wage})_i$ as a function of individual characteristics, X, and observed skills, θ^j:

$$\log(\text{wage})_i = f_m\Bigg(X_i, \theta_i^j\Bigg) \tag{20}$$

In this context, the wage return to skills can be calculated simply as $\frac{d\log(\text{wage})}{d\theta^j} = \frac{df_m\left(X_i,\theta_i^j\right)}{d\theta^j}$: this is the total wage return to skills, after controlling for individual characteristics. As I am considering starting wages, I do not include in this analysis the role of prior work experience (as in Ashworth et al., 2021).

I introduce two additional elements: (i) as skills are usually measured at the end of secondary schooling (i.e. between the age of 17 and 18, depending on the dataset and the country), they are endogenously determined by schooling choices, f^s and (ii) skills impact tertiary education, f^e.[24] Therefore, this would be a stylized, yet more detailed equation of wages, relative to Equation 20:

$$\log(\text{wage}) = f\Bigg(X, f^s, \theta^j, f^e\Bigg) \tag{21}$$

[24]Schooling choices f^s are determined by individual observed characteristics. While skills, θ^j, are endogenously determined by both observed characteristics and schooling choices. Tertiary education, f^e, is also influenced by individual observed characteristics, schooling choices, and skills.

Now, the returns to skills can be computed as:

$$\underbrace{\frac{d\log(\text{wage})}{d\theta^j}}_{\text{Total effect}} = \underbrace{\frac{\partial\log(\text{wage})}{\partial\theta^j}}_{\text{Direct effect}} + \underbrace{\frac{df^e}{d\theta^j}\frac{\partial\log(\text{wage})}{\partial f^e}}_{\text{Indirect effect}} \tag{22}$$

where the total effect is decomposed into a direct and indirect component of the impact of skills on wages. Undoubtedly, skills significantly influence tertiary education, which in turn has a consequential effect on wages. This framework provides a simple yet powerful approach applicable to diverse contexts in labor and education economics. It can be readily implemented using dynamic treatment effects models, enabling the estimation of treatment effects by considering counterfactual scenarios.

B.4 Counterfactual Simulation

To assess the treatment effects and establish confidence intervals, we employ a counterfactual simulation strategy (Cockx et al., 2019). In this approach, we conduct 999 simulations, randomly drawing parameters from the asymptotic normal distribution of the model's parameters. Subsequently, for each simulation draw, we utilize the probability types estimated through the EM algorithm to assign a heterogeneity type to each individual in the sample randomly. Based on these newly generated parameters, we simulate the complete sequence of schooling and labor market outcomes for each individual. We also employ this counterfactual simulation strategy to evaluate the model's quality by generating a comprehensive set of outcomes and comparing them to the observed outcomes in the data. This evaluation is presented in Section B.5. In most cases, the observed probabilities fall within the 95% confidence bounds of the simulated probabilities, indicating a good fit of the model to the observed outcomes in the dataset.

B.5 Goodness of fit tables

Table 25: Goodness of Fit - Models Demographic Cohorts

	M ((1987-1995)					Z (1996-2003)				
	Observed	Simulated	SE	95 CI		**Observed**	Simulated	SE	95 CI	
Grade Repetition (Primary Education)	**0.069**	0.072	0.008	0.056	0.087	**0.091**	0.094	0.010	0.073	0.114
School Recommendations	**2.926**	2.965	0.030	2.906	3.023	**2.617**	2.624	0.036	2.553	2.695
Grade Repetition (Secondary Education)	**0.148**	0.152	0.011	0.130	0.174	**0.148**	0.155	0.013	0.130	0.180
Secondary Education Enrollment	**2.226**	2.236	0.017	2.203	2.270	**2.244**	2.256	0.021	2.215	2.297
Cognitive Skills	**0.170**	0.174	0.021	0.132	0.216	**-0.191**	-0.193	0.025	-0.242	-0.144
Non-cognitive Skills	**-0.054**	-0.049	0.020	-0.088	-0.010	**0.060**	0.050	0.023	0.006	0.094
Social Skills	**-0.001**	0.007	0.021	-0.035	0.049	**0.001**	-0.006	0.024	-0.054	0.041
Secondary Education Diploma	**2.999**	3.044	0.024	2.997	3.091	**2.736**	2.776	0.031	2.714	2.838
Tertiary Education Enrollment	**0.575**	0.576	0.016	0.545	0.608	**0.329**	0.324	0.018	0.288	0.361
Tertiary Education Diploma	**0.759**	0.761	0.019	0.723	0.799	**0.443**	0.469	0.035	0.401	0.537
Wage Selection	**0.697**	0.700	0.015	0.671	0.730	**0.540**	0.546	0.018	0.510	0.581
Starting log hourly wages	**1.679**	1.680	0.021	1.639	1.721	**1.687**	1.693	0.028	1.639	1.748

C Results

C.1 Changes in Complementarities

Table 26: Distribution of Changes Across Cohorts by Skill Bundle

		$\theta^{sc} > 0$				$\theta^{sc} < 0$			
		M		Z		M		Z	
		Direct	Total	Direct	Total	Direct	Total	Direct	Total
$\theta^c > 0$	Skills	0.065	0.006	0.202**	0.144*	0.168***	0.103*	0.207**	0.145
		(0.056)	(0.050)	(0.081)	(0.082)	(0.060)	(0.056)	(0.093)	(0.090)
	Cognitive skills θ^c	0.096***	0.033	0.053	0.015	0.122***	0.066**	0.125***	0.088**
		(0.034)	(0.022)	(0.045)	(0.039)	(0.031)	(0.027)	(0.048)	(0.035)
	Non-cognitive skills θ^{nc}	0.011	-0.004	0.051	0.027	0.069**	0.052**	0.017	-0.005
		(0.036)	(0.021)	(0.043)	(0.036)	(0.035)	(0.026)	(0.050)	(0.040)
	Social skills θ^{sc}	-0.002	0.014	0.085**	0.073**	0.010	0.023	0.045	0.034
		(0.034)	(0.022)	(0.042)	(0.036)	(0.034)	(0.026)	(0.045)	(0.035)
$\theta^c < 0$	Skills	0.034	-0.015	0.174***	0.108*	0.174***	0.107**	0.177**	0.112
		(0.054)	(0.048)	(0.048)	(0.055)	(0.061)	(0.047)	(0.069)	(0.074)
	Cognitive skills θ^c	0.080**	0.014	0.057	0.024	0.122***	0.058**	0.131***	0.099**
		(0.035)	(0.026)	(0.037)	(0.035)	(0.042)	(0.027)	(0.042)	(0.039)
	Non-cognitive skills θ^{nc}	-0.003	-0.008	0.004	-0.022	0.068	0.053**	-0.026	-0.051
		(0.034)	(0.025)	(0.034)	(0.031)	(0.046)	(0.026)	(0.043)	(0.040)
	Social skills θ^{sc}	-0.010	0.017	0.087**	0.078**	0.013	0.033	0.043	0.034
		(0.037)	(0.029)	(0.036)	(0.033)	(0.042)	(0.028)	(0.042)	(0.038)

Notes: This graph includes the treatment effects of a σ increase to each skill by different skill bundles.

C.2 Model without Unobserved Heterogeneity

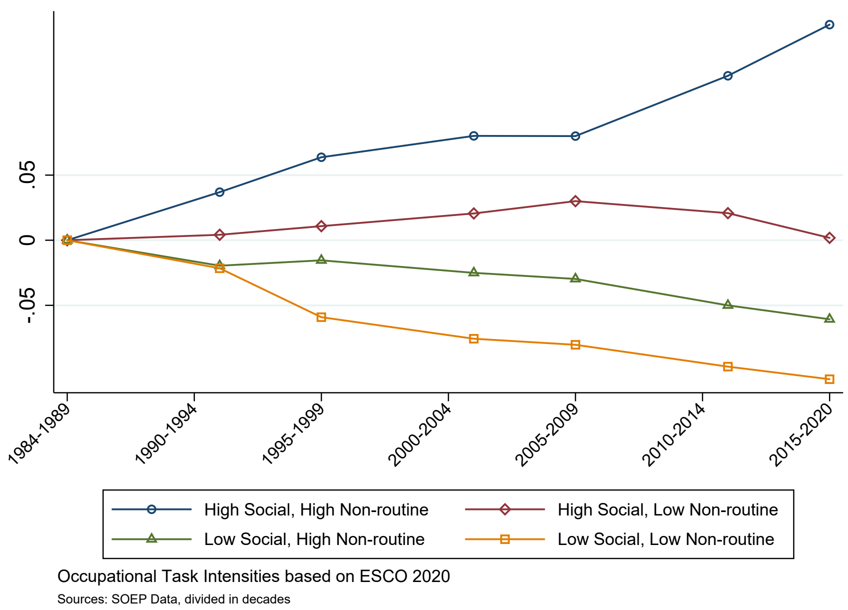
Table 27: Model accounting for unobserved heterogeneity

	M (1987-1995)				Z (1996-2003)			
	Without accounting for unobserved heterogeneity		Unobserved heterogeneity		Without accounting for unobserved heterogeneity		Unobserved heterogeneity	
	Total	Direct	Total	Direct	Total	Direct	Total	Direct
Skills	0.147***	0.052	0.112**	0.052	0.214***	0.170***	0.187***	0.123*
	(0.041)	(0.039)	(0.046)	(0.044)	(0.053)	(0.053)	(0.057)	(0.063)
Cognitive skills (θ^{c})	0.105***	0.036*	0.105***	0.044**	0.097***	0.060**	0.090***	0.055*
	(0.023)	(0.021)	(0.022)	(0.020)	(0.029)	(0.029)	(0.030)	(0.030)
Non-cognitive skills (θ^{nc})	0.042	0.014	0.038	0.025	0.004	-0.004	0.007	-0.017
	(0.026)	(0.019)	(0.023)	(0.018)	(0.030)	(0.026)	(0.029)	(0.028)
Social skills (θ^{sc})	0.001	0.004	0.002	0.021	0.069***	0.065***	0.066**	0.056**
	(0.025)	(0.018)	(0.025)	(0.020)	(0.025)	(0.023)	(0.029)	(0.027)
$\theta^{c}\theta^{nc}$	-0.003	-0.009	-0.026	-0.031	0.047	0.050*	0.030	0.033
	(0.030)	(0.021)	(0.024)	(0.020)	(0.032)	(0.028)	(0.031)	(0.029)
$\theta^{c}\theta^{sc}$	0.003	0.007	-0.007	-0.006	-0.002	0.001	-0.006	-0.005
	(0.029)	(0.023)	(0.027)	(0.022)	(0.029)	(0.028)	(0.029)	(0.026)

D Robustness Checks

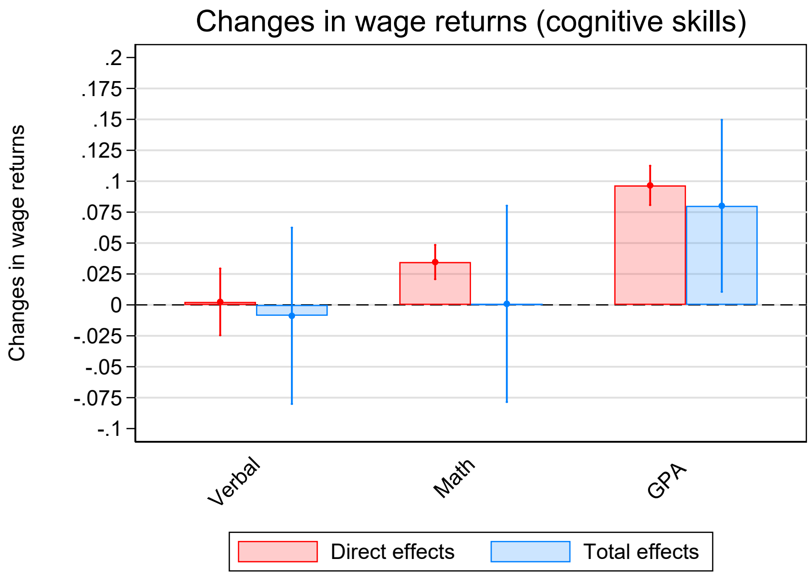
D.1 Task Content without Latent Factors

Figure 17: Relative Changes in Employment Share by Occupation Task Intensity



D.2 Changes in Returns to Multidimensional Skills

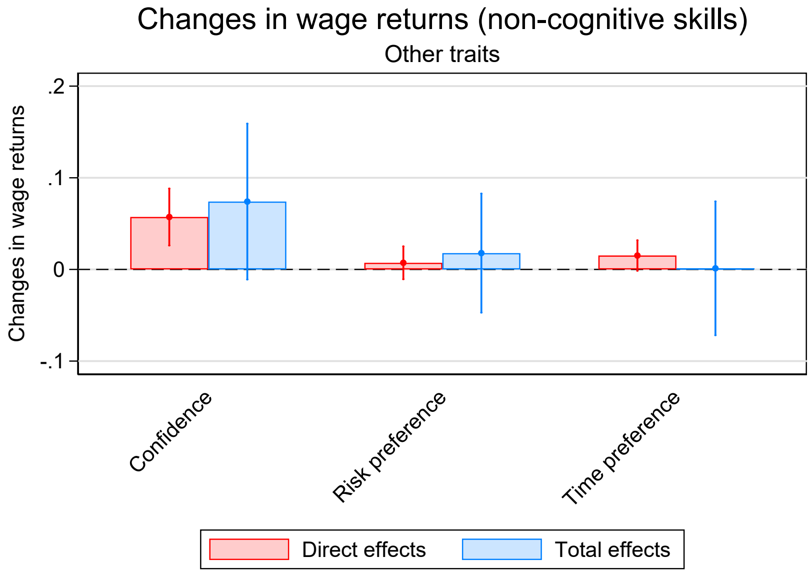
Figure 18: Changes in Wage Returns



Notes: Change, Δ_a^g, in wage returns across cohorts expressed in percentage points (p.p.). The change is the difference between cohort Z and M in the wage return to a σ increase in each specific skill. Direct effects do not include the indirect effects of education. Total effects include the composite effect of direct and indirect effects of a σ increase.

Figure 19 displays the additional non-cognitive skills considered in the analysis: confidence, risk preference, and time preference. Notably, there is a significant change in returns associated with confidence. Confidence is, again, one of the main predictor of social skills, validating my results.

Figure 19: Changes in Wage Returns



Notes: Change, Δ_a^g, in wage returns across cohorts expressed in percentage points (p.p.). The change is the difference between cohort Z and M in the wage return to a σ increase in each specific skill. Direct effects do not include the indirect effects of education. Total effects include the composite effect of direct and indirect effects of a σ increase.