Changes in Returns to Multidimensional Skills across Cohorts*

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January, 2025

Abstract

While social skills seem to gain importance in the workplace, other skills may become less relevant. The evolution in skill demand and supply affects returns to skills over time. Estimating returns is challenging: a bias comes from unmeasured ability, together with an indirect return through college. This paper estimates direct and indirect returns to skills, controlling for unmeasured ability, using a dynamic model with cognitive, social, and diligence skills. In Germany, across cohorts, returns to social skills grew by 6 percentage points. Due to routine-task displacement and sorting into routine-intensive occupations, returns to diligence skills dropped by 10 percentage points.

*I express my profound gratitude to Dieter Verhaest, Olivier De Groote, Jo Van Biesebroeck, and Koen Declercq for their guidance and support. This paper benefited greatly from helpful comments at various stages from Christophe Bruneel-Zupanc, Edwin Leuven, Hiroaki Kaido, Jared Ashworth, Philipp Schmidt-Dengler, Kristof De Witte, Frank Verboven, Hannah Zillessen, Gregory Veramendi, Costas Meghir, Pietro Biroli, Marco Bertoni, and several audiences at KU Leuven, Toulouse School of Economics, LEER Seminars, UCLouvain, University of Vienna, USI Lugano, Basel University, University of Verona, ROA Maastricht, the Workshop of the Fellows fRDB 2023, EALE Prague 2023, the 18th Belgian Day for Labour Economists, the European Winter Meeting of the Econometric Society 2023, SOLE Portland 2024, and other settings. Funding for this project was generously provided by the Research Foundation Flanders (FWO) - G079420N.

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1 Introduction

Technical change, globalization, and other factors are reshaping the labor market, modifying the demand and supply of skills with changes in return to skills over time. As measured by the college premium, return to skills has increased over several decades despite a significant rise in the supply of skilled workers (Goldin and Katz, 2008; Acemoglu and Autor, 2011). But, there are multiple dimensions of skills and recent findings showed that returns to social skills increased over time, while other skills became less relevant (Castex and Kogan-Dechter, 2014; Beaudry et al., 2016; Deming, 2017; Taber and Roys, 2019; Edin et al., 2022).[1] Individuals are endowed with multiple skills and the change in returns might be heterogeneous across different bundles, e.g. high cognitive individuals might receive higher returns to social skills (Deming, 2017). What are, then, the heterogeneous returns across the distribution of all possible skill bundles, and how have these returns evolved over time? Understanding this is essential for identifying those who benefit from, or are disadvantaged by, the changes in skill demand and supply.

A key methodological challenge is to identify returns to skills and skill bundle, while accounting that each skill measure might be a proxy for unmeasured ability, leading to a potential bias (Deming, 2017). Deming (2017) and Edin et al. (2022) addresses this by estimating returns to social and non-cognitive skills controlling, respectively, for years of completed education and college. But, education is endogenous to skills, and there is an indirect return through these channels. These variables are not fixed when the regressor of interest was determined: they are a "bad control" if we are interested in total returns (Angrist and Pischke, 2009).[2] Even if the focus is solely on direct returns, a bias comes from (dynamic) selection. If skills influence sorting into college, comparing wages by skill level within educational attainment is no longer valid, even with randomly assigned skill levels (Angrist and Pischke, 2009): for instance, low-cognitive individuals attaining a college degree will have higher levels of unmeasured ability.

This paper addresses these issues by developing a new dynamic model with endogenous multidimensional skills to estimate direct and total returns to skills and heterogeneous skill bundles, controlling for unmeasured ability differences. This approach makes several

[1] See Deming (2023) and Woessmann (2024) for detailed surveys on the topic of multidimensional skills.

[2] This happens because skills are usually measured before tertiary education, as in Deming (2017), Edin et al. (2022) and in the German Socio-Economic Panel Data (GSOEP). See Chapter 3.2.3 in Angrist and Pischke (2009).

contributions to the literature. First, it enables the estimation of heterogeneous returns across rich combinations of skill bundles, while controlling for unobserved heterogeneity (Aakvik et al., 2005; Heckman and Navarro, 2007). Unobserved heterogeneity, interpreted as exogenous unmeasured ability, can be identified using initial conditions, the panel structure of the data (Hu and Shum, 2012), local labor market conditions (Ashworth et al., 2021), and a set of exclusion restrictions, including school recommendations and reforms in Germany (Heckman et al., 2016; Ashworth et al., 2021; Humphries et al., 2023; Bruneel-Zupanc and Beyhum, 2024). Second, it identifies which specific skill bundles are becoming more or less rewarded in the labor market, while estimating both direct and total returns. To the best of my knowledge, this is one of the first papers to estimate returns to endogenous skills and skill bundles, which schooling or other interventions modify while controlling for exogenous unmeasured ability, which is, by definition, not modifiable.

Using data from the German Socio-Economic Panel (GSOEP), this paper analyzes the changes across demographic cohorts in return to three different skills: cognitive, diligence, and social. I estimate changes in returns to skills across cohorts using a dynamic model, as in Ashworth et al. (2021). Relative to Ashworth et al. (2021), this paper includes two recent demographic cohorts: Millennials (born in 1987-1995) and Generation Z (born in 1996-2003). Moreover, this paper includes one cognitive skill and two non-cognitive skills: social and diligence. This difference is relevant (see also Izadi and Tuhkuri, 2023). For instance, Deming (2017) considers "non-cognitive" skills that could capture diligence, but the evolution of these skills over time is unclear.[3] However, as Heckman et al. (2006) suggest, these skills are valued in specific labor markets, such as low-skilled. This may result in a different evolution over time relative to cognitive and social skills. Multidimensional skills are factors extracted using 156 measures from the GSOEP (see also Heckman et al., 2006; Cunha et al., 2010; Ashworth et al., 2021; Toppeta, 2022; Humphries et al., 2023). These measures include standardized cognitive tests, GPA, parental involvement, advanced 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).

[3] Deming (2017) builds a measure of non-cognitive skills using the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale.

Following the model in Acemoglu and Autor (2011), this paper links changes in skill returns over time to the evolution of the task content of occupations. Technology and globalization are "skill-biased" and can either complement or substitute workplace tasks (Autor et al., 2003). As individuals use their skills to perform these tasks, these factors directly impact skill demand.[4] A technical change may complement (substitute) specific tasks: this increases (decreases) the demand for skills with a comparative advantage in performing these tasks. A higher (lower) relative demand for skills increases (decreases) their returns. This approach contrasts with papers like Taber and Roys (2019), where skills and tasks are not treated as distinct concepts, and there is no sorting of individuals into occupations based on the matching between their skills and the task content of those occupations.

When considering multidimensional human capital, each multidimensional skill has a comparative advantage in different occupations, e.g. an extroverted individual in a job involving social interactions. Changes in the task content of occupations modify the comparative advantage of individuals. For instance, technology may substitute routine tasks while complementing social tasks. Higher productivity in social tasks leads to a greater employment share of social-task intensive occupations and implies a greater value of social skills, with higher returns (Deming, 2017). This paper tests this mechanism by measuring the task content of occupations in Germany between 1984 and 2020 using novel data from the European Skills, Competences, Qualifications and Occupations (ESCO). 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.

I find significant changes in the task content of occupations and skill demand. Consistent with Deming (2017), this paper finds evidence supporting the growing importance of occupations intensive in social tasks and a decline in routine tasks. Non-routine analytical (cognitive) task content remained relatively stable. Employment share surged by 18 percentage points for occupations emphasizing social tasks, regardless of their cognitive task content. At the same time, the employment share of routine-intensive occupations dropped. This change may be caused by recent technology and globalization (and other factors), substituting routine tasks while complementing social tasks. Social skills are be-

[4] Following Acemoglu and Autor (2011), a task is one unit of work activity that produces output. Thus, this approach emphasizes that skills are applied to tasks to produce output: skills do not directly produce output (Autor et al., 2003).

coming more important as workers are assigned to flexible problem-focused teams, rather than a factory assembly line (Deming, 2023).

Given the evolution in skill demand, there are significant changes in returns to multidimensional skills across cohorts. Using a dynamic model, I find a large and significant increase of 6.4 percentage points in the returns to social skills across cohorts. Higher complementarities between social and cognitive skills at the upper tail of the skill distribution drive this positive change, consistent with Deming (2017) and Weinberger (2014). In contrast with Castex and Kogan-Dechter (2014) and Edin et al. (2022), I did not find significant changes in the returns to cognitive skills. However, my analysis focuses on recent data and could fail to capture the effect of the decrease in demand for cognitive skill-intensive jobs, started in the early 2000s (Beaudry et al., 2016). At last, this paper contributes to the literature by showing that returns to diligence skills dropped substantially across cohorts. Low-cognitive individuals drive this result as they hold a comparative advantage in routine-intensive occupations. Furthermore, low-cognitive and high-diligence individuals do not experience a positive change in return to social skills.

These results 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). A new finding of this paper is that routine task displacement primarily harms low-cognitive individuals because of a substantial drop in returns to diligence skills. This finding connects to Acemoglu and Restrepo (2022), which shows that major changes in U.S. wage structure are accounted for by wage decline for groups of workers holding a comparative advantage in routine tasks in industries experiencing high automation. Regarding policy implications, there are potential distributional effects since this is one of the main drivers of rising income inequality (Acemoglu and Restrepo, 2022). Indeed, individuals high in cognitive and social skills are better off than those with low cognitive and high diligence skills, given routine task displacement. The results of this paper suggest that there might be a benefit to design policies aimed at supporting social skill training, especially for low-cognitive individuals or those who work in routine-intensive occupations and are likely to become unemployed.

Related Literature

This paper relates and contributes to several strands of the literature. First, it relates to the broader literature investigating the relationship between technical change and wages. One of the main points of this literature is explaining the rising skill premium (Tinbergen, 1974, 1975; Bound et al., 1992; Levy et al., 1992; Juhn et al., 1993; Acemoglu and Autor, 2011). Several papers have also documented a process of polarization, where employment and wages are growing at the ends of the skill distribution while falling at the middle (Autor et al., 2003; Autor et al., 2006; Acemoglu and Autor, 2011; Autor and Handel, 2013; Michaels et al., 2014; Lindenlaub, 2017; Bárány and Siegel, 2018). This phenomenon has been observed in the US and Europe (Goos and Manning, 2007; Dustmann et al., 2009; Goos et al., 2009, 2014). In these papers, skills are usually proxied by educational attainment. This paper differs as it considers the change in returns to multidimensional skills, relating to the growing literature that considers human capital to have multiple dimensions (Heckman et al., 2006; Guvenen et al., 2020; Lise and Postel-Vinay, 2020; Deming, 2023; Humphries et al., 2023; Izadi and Tuhkuri, 2023; Woessmann, 2024). Several papers have shown the importance of multidimensional skills, such as non-cognitive skills or personality traits, in the labor market (Lindqvist and Vestman, 2011; Lundberg, 2013; Humphries and Kosse, 2017; Todd and Zhang, 2020; Hermo et al., 2022; Humphries et al., 2023; Izadi and Tuhkuri, 2023). Others have provided evidence of changes in returns to multidimensional skills over time: there are lower returns to cognitive skills (Castex and Kogan-Dechter, 2014; Beaudry et al., 2016) and higher returns to social skills (Deming, 2017; Edin et al., 2022). My paper is closely connected to Deming (2017) and Edin et al. (2022). As described in the introduction, Deming (2017) and Edin et al. (2022) identify direct returns to skills, while controlling for educational attainment. This paper contributes to the literature by providing a model to estimate direct and indirect returns to skills while controlling for unmeasured ability differences. Following the literature (Deming, 2017; Edin et al., 2022; Deming, 2023; Woessmann, 2024), this paper estimates the effect of skills as measured (only) before starting college, without accounting for the (potential) skill development beyond this point. This paper addresses some of the broader concerns about skill measurement and dynamic selection, by including both unobserved ability and by estimating the indirect returns to skills, which may both partially capture this effect. Moreover, I use one cognitive and two non-cognitive skills: social and diligence. Using a dynamic model, I can estimate the returns to the full distribution of different multidimensional skill bundles. This paper establishes that, while social skills are growing, diligence skills are losing importance at work. Indeed, low-cognitive and high-diligence individuals are worse off because they sort into declining routine-intensive occupations, given that diligence skills have a comparative advantage in these occupations. My paper is also well-connected to Taber and Roys (2019), even if they focus only on less-educated men. They find that social skills have become much more important for this category, but they do not include in their analysis other non-cognitive skills. Moreover, they measure skill intensity using O*NET, while this paper includes measures of both skills and tasks, using data from GSOEP and ESCO, evaluating direct and indirect returns to skills across demographic cohorts and occupational sorting based on individual skills and tasks.

Second, it relates to the literature using a task-based approach. This approach is common in both employment polarization and changes in returns to multidimensional skills (Autor et al., 2003; Acemoglu and Autor, 2011; Deming, 2017; Edin et al., 2022). Focusing on the German context, Koomen and Backes-Gellner (2022), Spitz-Oener (2006), and Rohrbach-Schmidt and Tiemann (2013) have measured the task content of occupations. This paper contributes to this literature by developing a new measure of task content using data from ESCO and employing a latent factor approach. Unlike studies relying on questions from employer surveys, i.e. O*NET, this paper develops an approach incorporating an extensive list of thousands of objective task measures. ESCO is context-specific and readily applicable for cross-national analyses in Europe. This approach differs from papers, such as Edin et al. (2022) or Aghion et al. (2022), using O*NET, based on a survey of US workers, for European countries. Moreover, 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. At last, ISCO-08 occupations in ESCO are more detailed than the occupation classification from O*NET and, therefore, more precise.

Third, it relates to the literature on dynamic models of educational choices and labor market outcomes, starting from the seminal papers of Cameron and Heckman (1998) and Cameron and Heckman (2001). This paper uses a dynamic discrete choice model, estimating dynamic treatment effects (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Ashworth et al., 2021; Humphries et al., 2023). This approach has been applied by, among others, Colding et al. (2006), Belzil and Poinas (2010), Ashworth et al. (2021), Neyt et al. (2022), De Groote (2023), and Navarini and Verhaest (2023). A set of papers have introduced multidimensional skills in dynamic models (Guvenen et al., 2020; Lise and Postel-Vinay, 2020; Humphries et al., 2023) and estimated changes to returns across cohorts using a dynamic model (Ashworth et al., 2021). Ashworth et al. (2021) is a related paper, as it estimates a dynamic model for two cohorts while considering changes in returns to cognitive and non-cognitive skills. However, this paper differs as it is the first to model skills as endogenous while accounting for unmeasured innate ability. At last, using a dynamic model, I take a stance on the development of endogenous multidimensional skills through schooling, contributing to the literature on skill development (see 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 organized 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. This paper uses two primary sources of data: ESCO and GSOEP. Further details about the data are discussed in Section 6 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 usually lasts four years, provides a fundamental education in mathematics, German, and science.[5] Students usually receive instruction in all main subjects from a single teacher during this stage. Upon completion

[5] Six years in Berlin and Brandenburg.

of primary school, students move on to secondary school.[6]

At the end of primary school, schools recommend a track based on students' grades and attitudes. Individuals may receive a lower, intermediate, or upper secondary schooling recommendation.[7] 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 can choose the secondary school type.

Over the last decades, federal states in Germany have substantially reformed school recommendations: several states have abolished binding recommendations to replace them with non-binding ones, and vice versa, while others have switched back and forth (Grewenig, 2022). At this stage, children are assigned to one of three distinct tracks: the lower (basic) track (*Hauptschulabschluss*), the intermediate track (*Realschulabschluss*), or the upper (academic) track, which extends until grade 13 (or 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 potentially affect 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% 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.

[6]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).

[7]Some individuals may not receive a recommendation, or I may not observe the recommendation of individuals in the dataset; see Appendix 6.

2.2 Data

ESCO

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.

The ESCO is a dictionary of 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. Broader skill groups include these narrower skill descriptions. I reduce the dimensionality of this data by extracting three factors. These factors are measures of task content, following closely Deming (2017): routine, non-routine analytical (cognitive), and social tasks. Section 6 in the Appendix includes a detailed description of the latent factors approach used and of alternative measures used in Section 6 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. Table 1 includes a set of the top 10 ISCO-08 occupations sorted based on task content.[8]

[8] For instance, occupations intensive in social skills are, among others: "Policy administration professionals", "Sports, recreation and cultural centre managers" and "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".

GSOEP

The German Socio-Economic Panel (GSOEP) is a longitudinal micro-dataset in Germany, started in 1984. This paper uses the version of the data set that includes years up to 2020 (wave 37, SOEP, 2022). A Youth questionnaire was administered to all young people at 17 from 2000 on, which contained specific questions about education and skills.

The GSOEP includes a set of standardized tests for measuring cognitive skills and a set of measures of non-cognitive skills. The GSOEP's Youth Questionnaire contains data on 9,370 individuals, which can complement 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 the data, including the factors measuring multidimensional skills, can be found in Section 6 in the Appendix.

Table 2: Measurement 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 6 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 6 in the Appendix.

This paper includes cognitive and non-cognitive skills from the GSOEP (see also Humphries and Kosse, 2017). Regarding cognitive skills, I use data on standardized tests from the COGDJ questionnaire and information on secondary schooling GPA, advanced courses in secondary education, and parental involvement in school.[9] I use a large set of measures to identify two factors regarding non-cognitive skills. The large set of measures allows me to define two different factors: externalizing (social) and internalizing (diligence) 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 6 in the Appendix). I denote latent factors with θ: θ^c, θ^s, and θ^d denotes respectively cognitive, social, and diligence skills.[10] The latter measures discipline, conscientiousness, and internalized focus.[11] This paper studies 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 6 in the Appendix.

2.3 Exogenous Variables

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

Figure 1 shows the sorting and skill development patterns for individuals with different skills into secondary education tracks. Regarding θ^c, a clear pattern emerges. Those in the upper track exhibit higher cognitive skills than the mean. In contrast, the intermediate track aligns closely with the mean, while the lower track falls notably below the mean. These distributions may result from high-cognitive individuals sorting in the upper track.

[9] COGDJ questionnaire includes verbal, numerical, and figural standardized tests.

[10] Heckman et al. (2006) and Deming (2017) measure non-cognitive skills using a normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem scale. This paper utilizes 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.

[11] 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^d 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.

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.

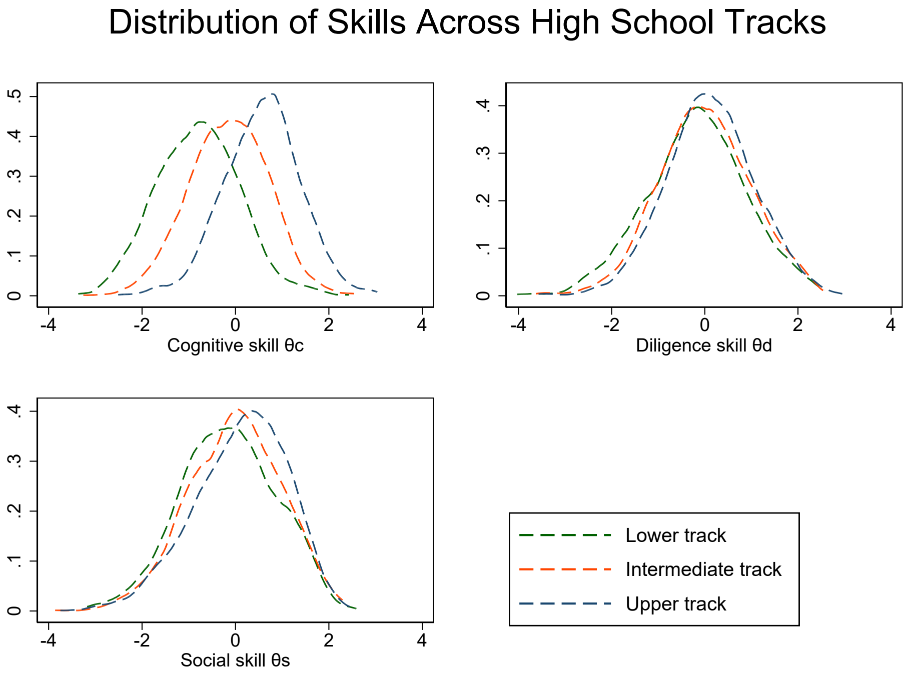
At the same time, it may also result from a focus on cognitive skill development in upper tracks relative to other tracks. Regarding θ^d and θ^s, the sorting pattern aligns with the one observed for θ^c but is less strong. Overall, on average, individuals in the upper track show higher skills in all three multidimensional skills.

2.4 Changes in Tasks

This paper analyzes the evolution in task content of occupation 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. Therefore, there is a single observation per individual for each half-decade.

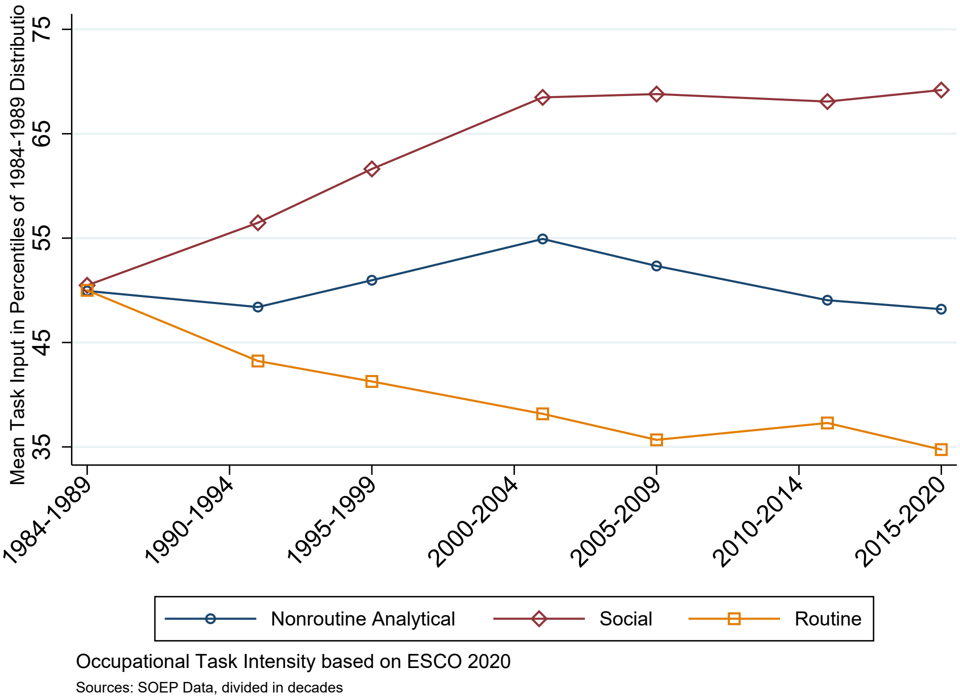
Following Deming (2017) closely, I ensure that each task measure variable has a mean of 50 centiles in 1984 and that the data are aggregated to the industry-education-sex level. This aggregation controls for changes in the industry and labor supply in the German economy. Indeed, subsequent movements should be interpreted as changes in the employment-weighted mean of each task relative to its importance in 1984. Figure 2 replicates both Figure I from Autor et al. (2003) and Figure III from Deming (2017) using data from the GSOEP and the ESCO.

Figure 1: Distribution of Skills across High-School Tracks



Notes: details on the latent factors used in this Figure are included in 6 in the Appendix. Latent factors θ are standardized to be mean 0 and standard deviation 1.

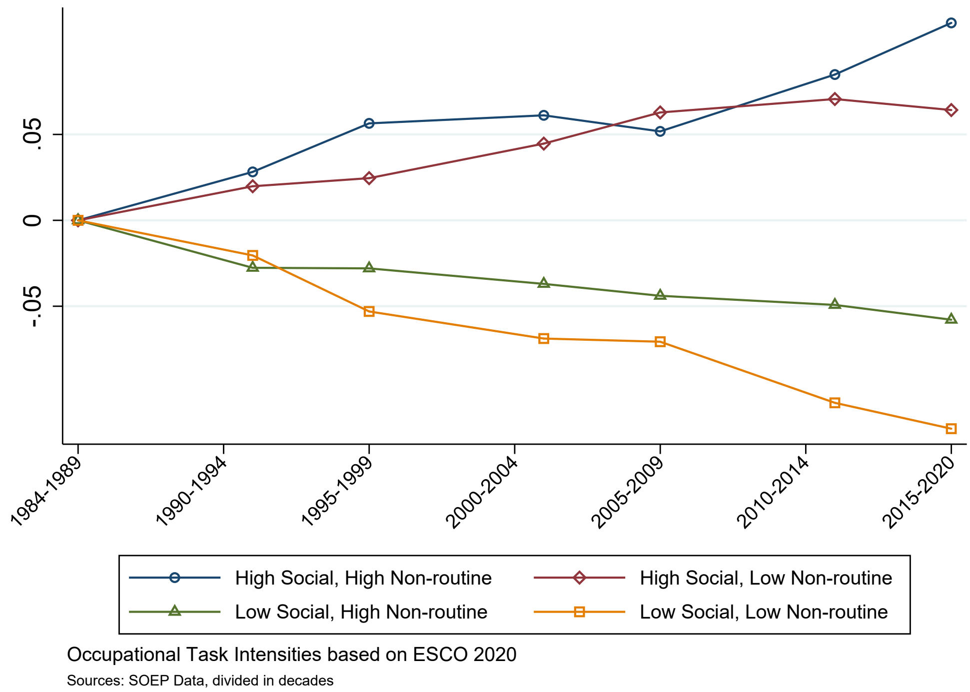
Figure 2: Worker Tasks in Germany, 1984-2020



Notes: Figure 2 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 6 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 task-intensive occupations. The labor input of routine tasks has declined over this period. Routine task input declined by a stark -30%, comparable to the US economy's results of Deming (2017). The decline in routine tasks mirrors the growing importance of social tasks in Germany's labor force between 1984 and 2020. Moreover, 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 is now at a stable level relative to 1984. This evolution is consistent with the sharp decline of non-routine analytical (cognitive) task measures observed by Beaudry et al. (2016) in the US from the early 2000s.

Figure 3: 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.

I control for possible skill upgrading 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).[12] I then compute the share of all labor supply-weighted employment in each category and year. Figure 3 shows that the employment share of occupations intensive in social tasks, regardless of their non-routine analytical task content, has grown by 18 percentage points from 1984. Also, there

[12]In Deming, 2017, possible skill upgrading may be the result of the high correlation between social and non-routine analytical (cognitive) skills task measures.

has been a significant decline in the employment share of low social, low cognitive intensive occupations. This change is fundamental in our setting, as it shows a substantial change in the demand for social and cognitive tasks between the early 2000s and the post-2010, which is the primary threshold between the two demographic cohorts in the analysis.

2.5 Tasks and Skills: Theoretical Framework

Following Acemoglu and Autor (2011), it is possible to formulate hypotheses regarding the returns on skills by examining the observed patterns in the evolution of the task content of occupations. Notably, this model offers a stark prediction. Suppose the relative market price of tasks where a particular skill group hold 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, through a productivity effect. In this setting, a rise (fall) in the skill demand will increase (decline) in the relative market price.[13]

Considering these three task measures, the relative market price of social tasks has increased over time, mirroring a significant decline in the relative market price of routine tasks. As these tasks have become more (less) important in the labor force, there has been a greater (weaker) demand for individuals with a comparative advantage in performing these tasks. This mechanism generates increasing returns over time. Therefore, I expect (i) an increase in the returns to social skills, as also predicted by the model of Deming (2017). However, other multidimensional skills also play a role. As the demand for non-routine analytical skill task measures has remained relatively 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 diligence skills, as individuals with high diligence skills may have a comparative advantage in performing routine tasks. Returns to diligence skills are conditional on both social and cognitive skills. As diligence skills, in this setting, are indicative of discipline, not being lazy, and conscientiousness, these hypotheses are in

[13] 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, their analysis shows that the relative wages of medium-skill workers formerly performing these tasks would fall. This paper does not consider measures of low to high-skilled workers but 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.

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). This way, low-skilled and high-routine jobs may have strong wage returns to higher values of diligence skills.

3 Identifying Returns to Multidimensional Skills

In this section, I develop a novel dynamic discrete choice model incorporating both endogenous skills and exogenous ability (see Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Ashworth et al., 2021; Joensen and Mattana, 2021; Humphries et al., 2023). Relative to Deming (2017) and Edin et al. (2022), using this model, I can estimate direct and total returns to skills, while controlling for unmeasured ability differences.

In Table 4, I estimate the returns to multidimensional skills and changes across cohorts using linear regression, including cohort-specific individual characteristics and educational choices. There are no changes across cohorts. Moreover, the returns to multidimensional skills are sensibly lower when including educational choices. This difference happens because post-measurement educational choices are not fixed when the regressors of interest, skills θ^j, are determined. This case exemplifies a "bad control" and, therefore, I can only estimate direct effects (Angrist and Pischke, 2009). However, when considering direct effects, there is a potential bias coming from (dynamic) selection: individuals with different skill levels within the same educational attainment are likely to have different unmeasured abilities (Angrist and Pischke, 2009). For instance, two individuals with different levels of cognitive skills who complete the same university are likely to be very different in their unobserved abilities.

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 "schooling" and after 17 as "school-to-work transition", as illustrated in Figure 4.

Skills θ are endogenous to schooling choices and individual characteristics. This underlines the potential impact of environmental factors on skill development. I assume that

Table 4: Preliminary Evidence: OLS Regression

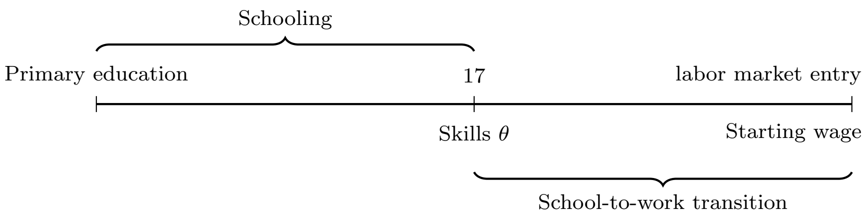
	Starting log hourly wage		
	(1)	(2)	(3)
Cognitive skills θ^c	0.162***	0.0776***	0.0284
	(8.58)	(3.51)	(1.40)
- Change across cohorts	-0.0768*	0.00944	0.0466
	(-2.49)	(0.26)	(1.37)
Diligence skills θ^d	0.0628**	0.0531**	0.0197
	(3.22)	(2.74)	(1.08)
- Change across cohorts	-0.0644*	-0.0560	-0.0116
	(-1.98)	(-1.72)	(-0.41)
Social skills θ^s	0.0281	0.00285	-0.00200
	(1.49)	(0.15)	(-0.11)
- Change across cohorts	0.0234	0.0513	0.0278
	(0.72)	(1.57)	(0.88)
Cohort-specific individual characteristics	No	Yes	Yes
Cohort-specific educational choices	No	No	Yes

Notes: estimates of returns to multidimensional skills and changes across cohorts using OLS. The model specification is:

$$\begin{aligned} w_i = {} & \beta_0 + \beta_1 \theta_i^c + \beta_2 \theta_i^d + \beta_3 \theta_i^s + \gamma_1 \text{Cohort}_i \\ & + \gamma_2 \theta_i^c \cdot \text{Cohort}_i + \gamma_3 \theta_i^d \cdot \text{Cohort}_i + \gamma_4 \theta_i^s \cdot \text{Cohort}_i \\ & + \delta \mathbf{X}_i \cdot \text{Cohort}_i + \varepsilon_i, \end{aligned}$$

, where in (1) $\mathbf{X}_i$ is empty, in (2) it only includes individual characteristics, and in (3) it also includes educational choices. This table includes, respectively: β_1, γ_2, β_2, γ_3, β_3, γ_4. All these parameters are cohort-specific. Individual characteristics included exogenous variables, as included in Table 3. Educational choices include endogenous educational outcomes: grade retention in primary and secondary education, high-school track diploma, higher tertiary education enrollment and diploma. Starting hourly wages are log wages for the first job of the individual. The sample is restricted to individuals with a wage, without including individuals who are not working. N is 2,219. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4: Timing



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 labor 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. This perspective aligns with contemporary findings in epigenetics, which emphasize the combined influence of genetics and the environment in shaping certain traits (Heckman, 2008). Once realized at 17, multidimensional skills affect both the last year of secondary education and tertiary education choices, together with labor 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: there is a dynamic behavior in skill development and education choices. In this dynamic setting, skills θ_i^j not only directly influence wages but also have indirect effects through educational outcomes.

Using this framework, I can estimate this model without actually solving the dynamic model. I do so by simulating the dynamic treatment effects: the impact of choice at a given time on future choices and outcomes (Heckman et al., 2016; Humphries et al., 2023). Nonetheless, an important limitation of this approach is that it allows only ex-post simulation. It does not allow me to calculate the impact of treatments that do not enter directly into the observed state variables.

3.2 Dynamic Discrete Choice Model

Starting from this general framework, I set up a model of joint educational choices, skill development and labor market outcomes to estimate the dynamic treatment effects of skills. This model corresponds to an underlying dynamic discrete choice problem (Humphries et al., 2023). In each period $t = \{0, ..., T\}$, individuals have a set of observed state variables s_t, and choose a decision $d_t \in \{1, ..., D_t\}$. In period t, individuals maximize their expected utility:

$$\mathbb{E}\left[\sum_{k=0}^{T-k} \beta^k U\Big(d_{t+k}, s_{t+k} | d_t, s_t\Big)\right] \tag{3}$$

Equation 4 includes the dynamic programming problem of the individual:

$$V(s_t) = \max_{d_t \in D_t} \left(U(d_t, s_t) + \beta \int V(s_{t+1}) dF(s_{t+1} | d_t, s_t) \right), \tag{4}$$

with the choice-specific value function:

$$v(d_t, s_t) = U(d_t, s_t) + \beta \int V(s_{t+1}) dF(s_{t+1} | d_t, s_t), \tag{5}$$

where s_t may include h_t observed state variables, η unobserved state variables, and ε_t shocks. Following Humphries et al. (2023), Arcidiacono and Miller (2011), and Hotz and Miller (1993), I can write the probability of choosing the specific choice $d_{j,t}$ in period t as

$$\Pr(d_{j,t} | h_t, \eta) = \int I\left\{ \underset{d_t}{\operatorname{argmax}} [v_t(d_t, h_t, \eta) + \varepsilon_t(d_t)] = d_{j,t} \right\} dG_\varepsilon(\varepsilon_t), \tag{6}$$

under two assumptions: (i) the unobservable shocks are i.i.d. over time and across individuals with distribution G_ε, and (ii) the state transition variables depend only on the previous period, but not on the shocks from the previous period (Hotz and Miller, 1993; Rust, 1994; Arcidiacono and Miller, 2011; Humphries et al., 2023). Under these assumptions, the joint probability of a given set of states and actions can be estimated non-parametrically from the data.[14]

3.3 Model

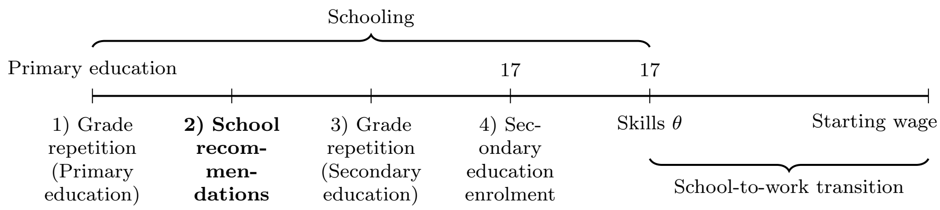
Using this framework, I can estimate the model without actually solving the complete forward-looking dynamic model, as described in Section 3.2. I do so by simulating the dynamic treatment effects: the impact of choice at a given time on future choices and outcomes (Heckman et al., 2016; Humphries et al., 2023). Nonetheless, an important

[14]This is achieved by imposing assumptions used for conditional choice probabilities (CCP) estimation of fully-specified dynamic discrete choice models (Humphries et al., 2023).

limitation of this approach is that it allows only ex-post simulation. It does not allow me to calculate the impact of treatments that do not enter directly into the observed state variables.

In this model, each individual $i \in I$, a member of demographic cohort c, undergoes a process of dynamic human capital accumulation. Following Ashworth et al. (2021), the model is estimated separately for each demographic cohort c. For the sake of clarity, subscript c is suppressed in subsequent equations.[15]

Figure 5: Model: Schooling Phase



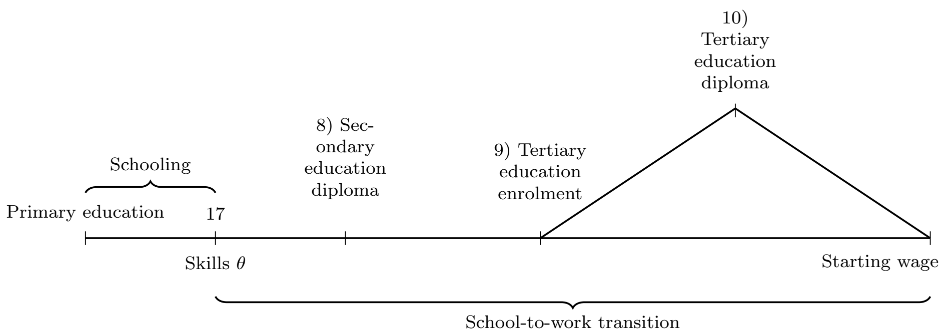
I model choices from primary education to entry into the labor market. Let t denote the sequence of choices and outcomes in the model. Before skill measurement, there is a set of choices during the schooling phase, as shown in Figure 5. At $t = 1$, students repeat a grade in primary education or not, $D_1(\kappa_1)$, where $\kappa_1 \in \mathcal{K}_1 = \{0, 1\}$, with $\kappa_1 = 1$ defining repeating a grade. This depends upon time-unvarying observed characteristics (X_i) and t-specific local labor 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 labor 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 $\kappa_4 = \kappa_2 \in \mathcal{K}_2$.

[15]The model should always be interpreted as cohort c specific

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 $j \in \{c, d, s\}$ denoting cognitive, diligence 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 6 describes. Each skill θ_i^j for $j \in \{c, s, d\}$ is endogenous into the dynamic model. These factors are estimated in a first stage. See further details in Section 6 in the Appendix. Each skill θ results from a development process starting as early as schooling. Moreover, local unemployment may influence skills development as an external shock. Schooling choices and early schooling performances, such as grade retention or track enrolment, also influence skill development.

Figure 6: 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 enrolling ($D_9(\kappa_9) = 1$), they can obtain a diploma ($D_{10}(\kappa_{10})$). At last, individuals choose to enter the labor 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 $I_{t\kappa_t}$, where individual i subscripts are suppressed, and t is the sequence of choices and outcomes in the model.[16] $I_{\kappa_t}^t$ depend on time-unvarying exogenous variables (X_i), time-varying local labor market

[16] Because these choices are sequential, t is clearly linked to time.

conditions (L_i^t), t-specific endogenous outcomes (Z_i^t), and a residual term, e_i^t, that captures an unobserved component from the econometrician point of view. I approximate this latent utility function $I_{t\kappa_t}$ to be a linear function:

$$I_{\kappa_t}^t = \beta_{0t} + \beta_{Xt}X_i + \beta_{Lt}L_i^t + \beta_{Zt}Z_i^t + e_i^t \text{ for } t \in \{1, 2, 3, 4, 8, ..., 11\} \tag{7}$$

The discrete choices of the model are characterized by the maximization of a latent utility variable $I_{t\kappa_t}$.

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

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

$$Y_i^t = \beta_{0t} + \beta_{Xt}X_i + \beta_{Lt}L_i^t + \beta_{Zt}Z_i^t + e_i^t \text{ for } t \in \{5, 6, 7, 12\} \tag{9}$$

Log hourly wage $Y_{i12} = \log(wage)_i$ at the first job after the end of education is a linear function:

$$\log(wage)_i = \beta_{0t} + \beta_{Xt}X_i + \beta_{Lt}L_i^t + \beta_{Zt}Z_i^t + e_i^t \text{ for } t \in \{12\} \tag{10}$$

I use starting log hourly wages to remove the possible influence of endogenous work experience. Z_i^{12} also includes a set of skill complementarities, dynamic complementarities with educational outcomes, and skill-ability complementarities.[17]

I use starting wages because of there might be a differential skill development on the job, which I cannot directly observe given that I only observed skill measures at age 17. Moreover, relative to this, I estimate only the effects of age 17 skills on subsequent wage outcomes, which is a combined effect of changes in the development of skills after age 17 and changes in the value of skills. In this respect, there might be two main channels: (i) skills at 17 might be endogenously determined by schooling choices, but the development after the age of 18 might only be marginal. Therefore, we could consider the development of skills after the age of 17 as fixed. (ii)

At this point, I am estimating a special case of the standard forward-looking dynamic

[17]This includes (i) multidimensional skills, θ^j for $j \in \{c, s, d\}$, (ii) skill complementarities ($\prod_j^J \theta^j \theta^c$ for $J = \{s, d\}$, (iii) a cubic polynomial in multidimensional skills, (iv) a cubic polynomial in skill complementarities, (v) interactions between skills and high-school track, tertiary education enrollment and diploma, (vi) interactions between secondary and tertiary education diploma (educational pathways), and (vii) interactions between skills and educational pathways.

discrete choice model, as described in Section 3.2, where the discount factor (β) is set to zero, effectively eliminating forward-looking behavior. Under this assumption, each equation could potentially be estimated separately. However, this approach relies on a strong assumption that may be unrealistic, particularly in the context of educational choices and skill development, where forward-looking behavior is likely to be significant. Then, to recover forward-looking behavior, I follow the literature on dynamic treatment effects and I estimate dynamic treatment effects based on Equation 6, which includes observed state variables ($h_t = (X_i, L_i^t, Z_i^t)$), ε_i^t shocks and, at last, η unobserved state variables (Heckman and Navarro, 2007; Humphries et al., 2023).

3.4 Unobserved Heterogeneity and Identification

Unobserved heterogeneity is crucial in identifying dynamic treatment effects models because it induces correlation across different choices, addressing the issue of dynamic selection. The literature calls this matching on unobservables relative to matching solely on observables (Heckman and Navarro, 2007). Indeed, choices and outcomes of the model are correlated and this rationalizes the difference in output between observationally identical individuals (Aakvik et al., 2005).

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 better schooling or labor market outcomes.[18] I apply the following factor structure to the error term e_i^t:

$$e_i^t = \gamma_{mt}\eta_m + \varepsilon_i^t, \tag{11}$$

in which η_m is a random effect, independent of ε_i^t, 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

[18] 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, even when having exactly the same observed characteristics. 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).[19] 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), Heckman et al. (2018a), Heckman et al. (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, the 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 (see Appendix Table 27). A binding or a non-binding system affects 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 (see Appendix Table 28). There is a large unexplained variation among individuals who, for instance, received a lower school recommendation but still enrolled in upper schooling and managed to develop higher skills, e.g., cognitive (see Appendix Figure 19). 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 enrollment, as either way (binding or non-binding reforms), it will induce individuals into a specific

[19]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.

track. Lastly, as the unemployment rate at the state level is a time-variant variable and t-specific, it works as 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).

Moreover, the combined use of these exclusion restrictions with the unemployment rate at the district level is necessary to correctly identify unobserved ability, as explained by Bruneel-Zupanc (2023) and Bruneel-Zupanc and Beyhum (2024). School recommendations by teachers are considered to be a quasi-IV (Bruneel-Zupanc, 2023). These are relevant but possibly invalid IV, because they are not exogenous or fully excluded. For instance, in our framework, school recommendations are proxies of unobserved (innate) ability, but, as implied in our model, they do not affect wages, after controlling for educational attainment and unobserved ability itself. However, they remain relevant: after controlling for unobserved ability, a better school recommendation will still imply a higher probability of completing a higher educational attainment. Bruneel-Zupanc and Beyhum (2024) shows that it is possible to achieve identification by complementing this possibly endogenous quasi-IV with an exogenous but possibly included quasi-IV. In this case, an exogenous but possibly included quasi-IV can be exogenous shocks to local labor market, such as unemployment rates, at the time of the decisions of educational choices.

3.5 Likelihood Function

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

$$\ell_{it} = \begin{Bmatrix} \frac{1}{\sigma_o}\Phi(\frac{Y_{it}^{'}}{\sigma_o}) & \text{if continuous} \\ \Lambda(I_{\kappa_t}^t) & \text{if discrete} \end{Bmatrix} \qquad \text{for } t \in T, \tag{12}$$

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.[20]

Without including unobserved heterogeneity ($v_{it} = \varepsilon_{it}$), the likelihood $\mathcal{L}_i$ of the model

[20] Where $Y_{it}^{'} = \beta_{0t} + \beta_{Xt}X_i + \beta_{Lt}L_{it} + \beta_{Zt}Z_{it}$ for $t \in T$.

is constructed using the full set of outcomes, and it is fully separable:

$$\log(\mathcal{L}_i) = \sum_{i=1}^{I} \log\left(\prod_{t=1}^{T} \ell_{it}\right) = \sum_{i=1}^{I}\sum_{t=1}^{T} \log(\ell_{it}) \tag{13}$$

Therefore, it can be estimated in separate stages, with consistent results.[21] However, when introducing unobserved heterogeneity ($v_{it} = \gamma_{mt}\eta_m + \varepsilon_{it}$), the likelihood is not separable anymore, and the optimization problem becomes:

$$\{\hat{\gamma}, \hat{\pi}\} = \arg\max_{\gamma,\pi} \sum_{i=1}^{I} \left[\sum_{m=1}^{M} \pi_m \log\left(\prod_{t=1}^{T} \ell_{it}(H_t, \gamma_{mt}, \varepsilon_t)\right)\right], \tag{14}$$

where there is a number of M unobserved types, and I need to estimate both the probability types associated with each unobserved type m, π_m, and the m specific parameter for each outcome t. H_t includes observed state variables 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 in the Appendix. I evaluate the model optimization and the number of heterogeneity types in Section 6 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 6 in the Appendix for the definition of the treatment effects. See Section 6 in the Appendix for further information on the simulations for estimating counterfactuals.

4.1 Changes in Returns to Skills

In this section, I estimate direct and total returns to skills and relative changes across demographic cohorts, M (1987-1995) and Z (1996-2003). The analysis focuses on estimating returns to one standard deviation (σ) increase in cognitive, diligence, and social skills.[22]

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

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

While direct returns to skills exclude the dynamic effects occurring during the school-to-work transition phase, total returns capture both the direct effects and the indirect effects going through skill development's influence on educational choices (See Appendix section 6).

For each cohort $c \in \{M, Z\}$, I estimate the direct, $g = dt$, and the total, $g = tt$, return to a σ increase for each skill θ^j, with $j \in \{c, s, d\}$:

$$\Delta^g_{\theta^j,c} = f^w_{mg}(\theta^j_i + \sigma) - f^w_{mg}(\theta^j_i) \quad \text{for } g \in \{dt, tt\} \text{ and } j \in \{c, s, d\} \tag{15}$$

Table 5: Wage Returns to a σ Increase in Multidimensional Skills

	(1) M (1987-1995)		(2) Z (1996-2003)	
	Direct	Total	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)
Diligence skills (θ^d)	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^d, and θ^s), including the effect of complementarities.

Table 5 includes returns, $\Delta^g_{\theta^j,c}$. "Skills" denotes a σ increase in all multidimensional skills: from a total (direct) return of 11.2% (5.2%) for individuals in demographic cohort M (1987-1995), I observe a total (direct) return of 18.7% (12.3%) for individuals in demographic cohort Z (1996-2003). Cognitive skills, θ^c, have the largest direct and total returns: 4.4% and 10,5 % for individuals in M and 5.5% and 9% for individuals in Z. These returns 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 further educational returns. The returns to diligence skills, θ^d, are not significant. The returns to social skills are not significant for individuals in M. However, the returns are significant for individuals in Z: a σ increase in social skills is associated with a 6.6% increase in hourly wages. Most of this effect is accounted for by direct effects, without considering the indirect effect of education. Therefore, this may be interpreted as a change in the labor market setting, as in Deming (2017). In Appendix Table 29, I include the difference between direct and total returns: total returns are significantly higher than direct returns by 6 percentage points.

Without accounting for exogenous ability, returns to endogenous skills differ, as shown in Table 6. I only find significant and positive returns to cognitive skills when including

Table 6: Wage Returns to a σ Increase in Multidimensional Skills

	M (1987-1995)				Z (1996-2003)			
	Without exogenous ability		Exogenous ability		Without exogenous ability		Exogenous ability	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Skills	-0.031	0.020	0.052	0.112**	0.129*	0.189***	0.123*	0.187***
	(0.053)	(0.054)	(0.044)	(0.046)	(0.072)	(0.065)	(0.063)	(0.057)
Cognitive skills (θ^c)	0.010	0.074**	0.044**	0.105***	0.010	0.047	0.055*	0.090***
	(0.026)	(0.029)	(0.020)	(0.022)	(0.039)	(0.038)	(0.030)	(0.030)
Diligence skills (θ^d)	-0.017	-0.009	0.025	0.038	0.008	0.033	-0.017	0.007
	(0.025)	(0.029)	(0.018)	(0.023)	(0.034)	(0.035)	(0.028)	(0.029)
Social skills (θ^s)	0.013	-0.011	0.021	0.002	0.081**	0.091**	0.056**	0.066**
	(0.028)	(0.033)	(0.020)	(0.025)	(0.035)	(0.036)	(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^d, and θ^s), including the effect of complementarities. I estimate returns to a σ increase in each skill without exogenous abilities, by simulating the results with only one unobserved type in the model. When including two unobserved types, I define the results as including exogenous abilities.

exogenous ability. On the other side, including exogenous ability reduces the positive and significant effect of social skills for demographic cohort Z, which remains positive.

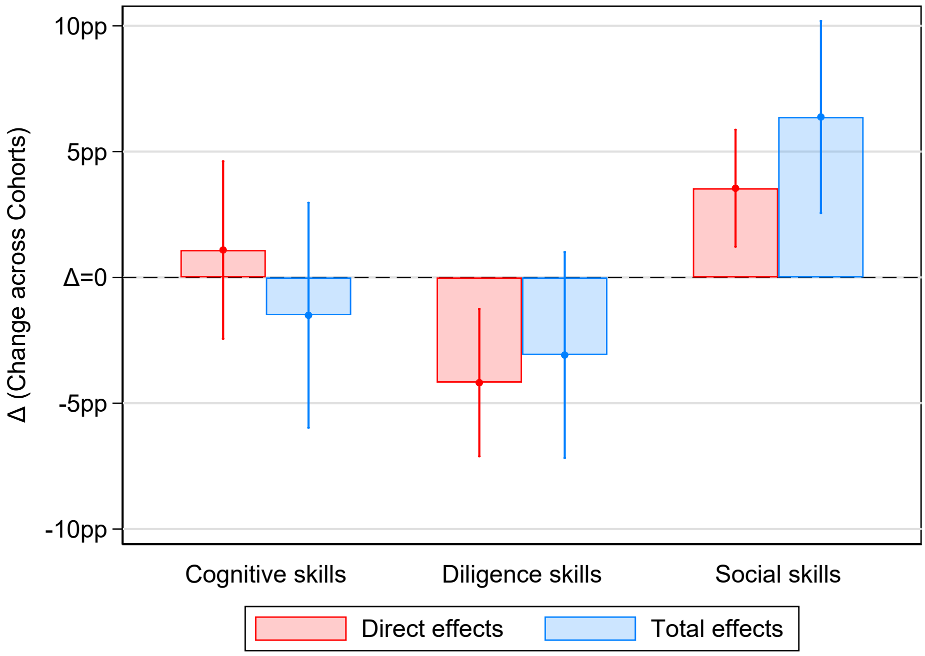
Using estimated returns, I can retrieve the changes across cohorts M and Z:

$$\Delta^g_{\theta^j} = \Delta^g_{\theta^j,Z} - \Delta^g_{\theta^j,M} \quad \text{for } g \in \{dt, tt\} \text{ and } j \in \{c, s, d\} \tag{16}$$

Figure 7 includes changes in returns across cohorts. This figure shows the change in percentage points in wage returns to skills across cohorts.

Which skills yield higher (lower) returns? Cognitive skills are stable over time, and no significant change exists across cohorts. While social skills gained in importance, diligence skills became less relevant. The returns to social skills have increased by 6.4 percentage points across these two cohorts, consistent with Deming (2017). Diligence skills show a downward trend in wage returns, with a negative change of 4.2 percentage points in direct effects. These results may unmask consistent heterogeneity based on the skill bundle of each individual. Overall, these results largely align with the prediction made by the model

Figure 7: Changes ($\Delta^{g}_{\theta^j}$) in Wage Returns to Multidimensional Skills across Cohorts



Notes: Changes in wage returns are computed in percentage points (pp). This is the change (Δ) computed across demographic cohorts. $\Delta = 0$ represents no change across cohorts in the returns to skills.

of Acemoglu and Autor (2011) in Section 2.4.

However, it is important to note that this analysis does not account for the (potential) dynamic development of skills during the school-to-work transition phase (6), after the age of the measurement (17 for the GSOEP), as in other papers in the literature (Deming, 2017; Edin et al., 2022). Consequently, the estimated returns should be interpreted solely as returns to skills as measured at age 17 for each individual, unless it is assumed that skill development after age 18 is only marginal and that skill measurement at age 17 reasonably proxies each individual's skill endowment entering the labor market. Any subsequent effects on skill development or complementarities emerging after this point would not be captured by the direct effects but may be partially reflected in the total returns.

Additionally, as the analysis is based solely on starting wages, it does not provide insights into the future evolution of skill returns beyond the first job. However, this approach offers a clear estimation of skill returns, while mitigating the influence of differential skill development or training choices made during early career stages.

4.1.1 Changes in Complementarities and Heterogenous Effects

In this section, I further document the role of complementarities and heterogenous effects. The model includes substantial heterogeneity and complementarities, both dynamic and skill complementarities, with heterogeneous returns to skill and non-linearities. This model allows me to estimate changes in returns considering selected skill bundles. I compute the return to a σ increase in diligence (θ^d) and social (θ^s) skills, given cognitive (θ^c) skills fixed at each point of the distribution. Equation 17 is used to compute the change in returns to θ^q for $q \in \{s, d\}$ at each fixed point n of the distribution of θ^c and each point nn of θ^q:

$$\begin{aligned} \Delta^{n,nn}_{\theta^q,\theta^c,\theta^{-q}} &= \\ \frac{1}{I}\sum_{i=1}^{I}\Bigg(\bigg(f^w_{mZ}(\theta^q_{iZ} = nn+\sigma|\theta^c_Z = n, \bar{\theta}^{-q}_Z) - f^w_{mZ}(\theta^q_{iZ} = nn|\theta^c_Z = n, \bar{\theta}^{-q}_Z)\bigg) - \\ \bigg(f^w_{mM}(\theta^q_{iM} = nn+\sigma|\theta^c_M = n, \bar{\theta}^{-q}_M) - f^w_{mM}(\theta^j_{iZ} = nn|\theta^c_M = n, \bar{\theta}^{-q}_M)\bigg)\Bigg) \\ \text{for } q \in \{s, d\}, \end{aligned} \tag{17}$$

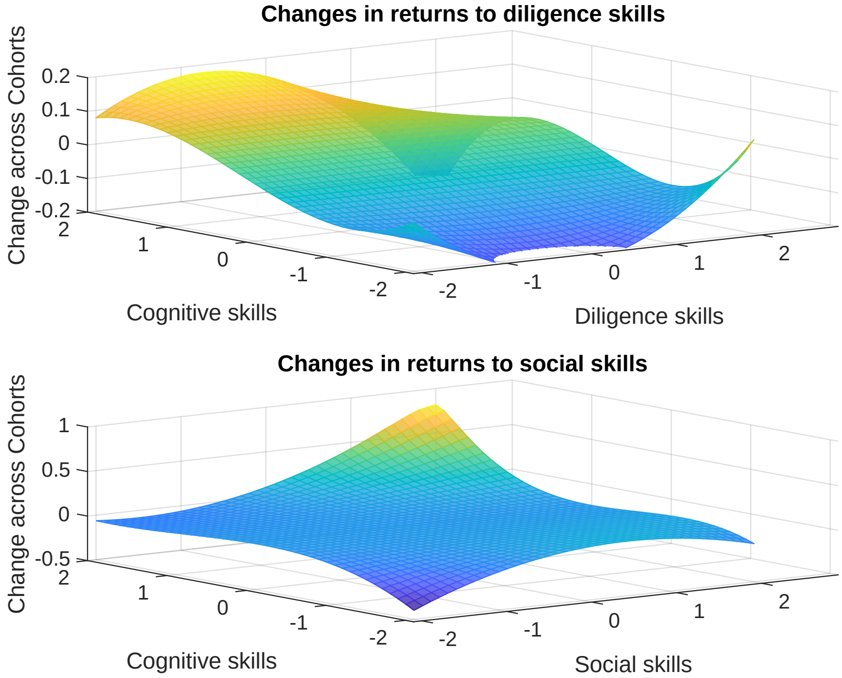
where both n and nn are included in $\{-2, ..., 2\}$. θ^{-q} represents the remaining skill, when considering θ^q (e.g. in the computation for θ^d, $\theta^{-q} = \theta^s$). The output is a matrix represented in Figure 8.[23]

Figure 8 shows that there is a substantial increase in social and cognitive skill complementarity (Deming, 2017). This result is evident from Figure 8, where the most significant changes in the returns to θ^s, are concentrated among θ^c and θ^s above the mean. Increasing complementarity between cognitive and diligence skills is concentrated on the left side of the diligence skill distribution. In Figure 8, the most considerable return change is concentrated between individuals with cognitive skills larger than 1σ and individuals with diligence skills comprising- -2σ and 0.

Figure 9 further investigates this by including the changes in returns to both diligence and social skills across the entire skill distribution for individuals with either low ($\theta^c < 0$) or high ($\theta^c > 0$) cognitive skills. In Figure 9, the horizontal black line ($\Delta = 0$) represents

[23] 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 8: Distribution of Changes in Wage Returns to a σ Increase across Cohorts



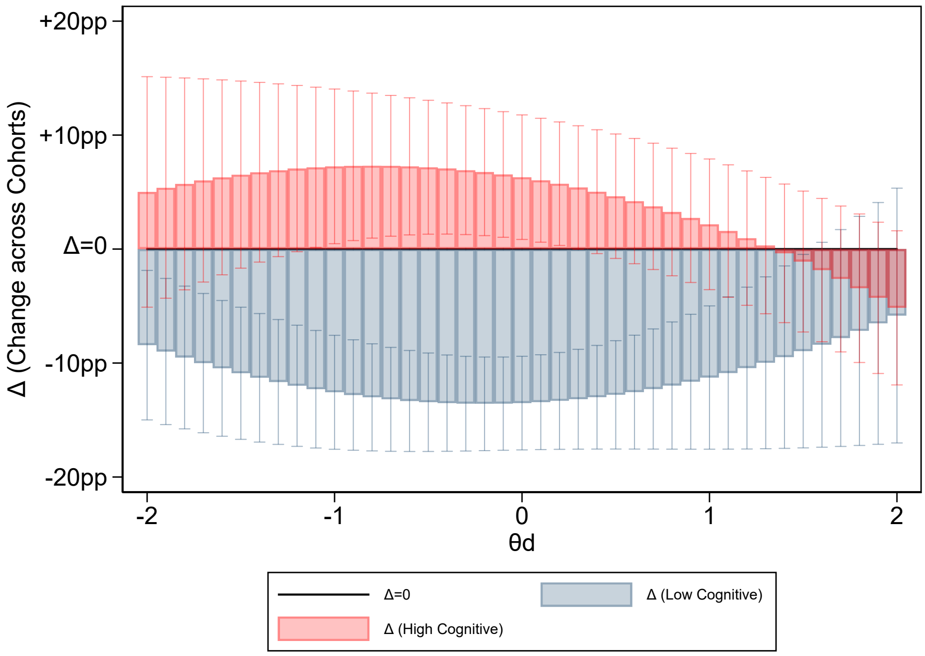
Notes: This graph is the result of a simulation for which we compute a σ increase at each point of the matrix computed using combinations of two skills while holding fixed the other skill (at mean). For each return, I compute the change across demographic cohorts. Skills are standardized to be distributed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

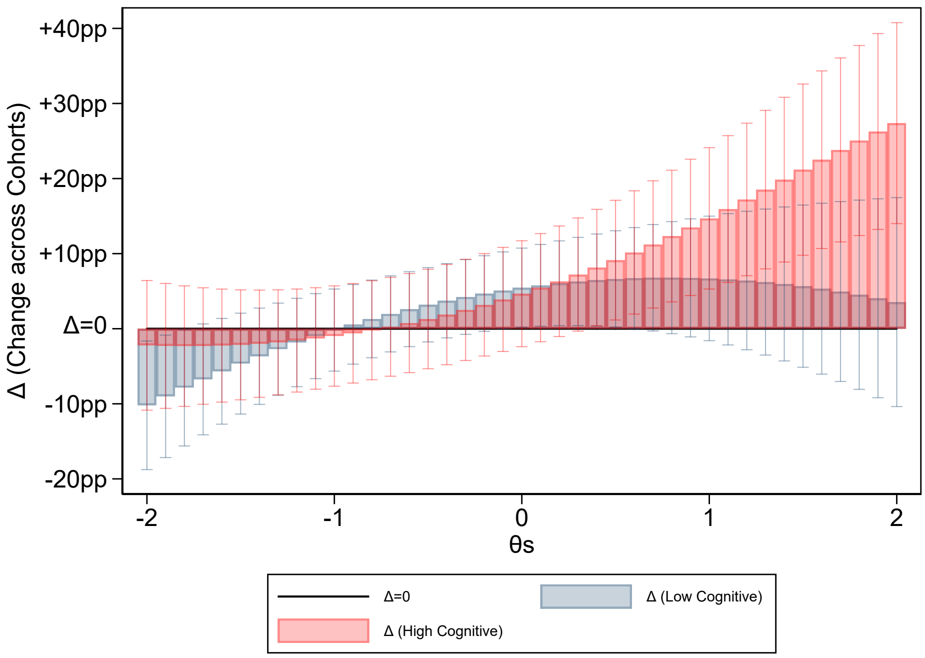
no changes across cohorts in the returns to a σ increase in skills. Further, Figure 9 includes the Δ across cohorts in returns for high ($\theta^c > 0$) and low ($\theta^c < 0$) cognitive individuals, respectively in red and blue. Each bar represents the change across cohorts in returns to a $+1\sigma$ at each distribution point while holding the other skill fixed. Individuals with high cognitive skills benefit from higher returns to diligence skills, except when the latter is well above the mean. There are no significant negative changes in returns to diligence skills for high-cognitive individuals. The downward trend in returns to diligence skills is driven by individuals with low cognitive skills, with large and negative changes in returns to diligence skills across the entire distribution.

Regarding social skills, the relationship is not substantially different for individuals with different cognitive skills. However, individuals with high cognitive skills benefit the most from higher returns to social skills when they have social skills above the mean.

Individuals who have a comparative advantage in routine tasks (high diligence skills and low cognitive skills) essentially experience declining returns regardless of where they sort, as they have a comparative advantage in performing a set of tasks, which is declining (Acemoglu and Autor, 2011). In Table 7, I further show the heterogeneity in returns to

Figure 9: Changes (Δ) in Returns across Cohorts in percentage points (pp) on the Distribution of Diligence (θ^d) and Social (θ^s) Skills for Low ($\theta^c < 0$) and High ($\theta^c > 0$) Cognitive Individuals





Notes: This graph includes the changes across cohorts in the return to skills at each point of the skill distribution while keeping the other multidimensional skills constant. You can find the formula used in the main text, alongside with a 3D graph showing the full result. I consider individuals with high ($\theta^c > 0$) or low ($\theta^c < 0$) cognitive skills, by averaging the changes across cohorts. Confidence intervals are computed at the 95% level. All confidence intervals are computed relative to $\Delta = 0$, i.e. no change across cohorts.

a σ increase in each skill by considering different bundles of skills.[24] The estimation in Figure 9 excludes the effect of one of the two non-cognitive skills for clarity. The following tables include the full skill bundle with the relative complementarities effects.

Table 7: Changes (Δ) in Returns across Cohorts by Skill Bundle

		$\theta^d < 0$				$\theta^d > 0$			
		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)
	Diligence skills θ^d	-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)
	Diligence skills θ^d	-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. θ^j with $j \in J \in \{c, d, s\}$ represents cognitive, diligence, and social skills. "Skills" include the combined effect of a σ increase in each skill.

The analysis of Table 7 reveals a substitution effect occurring within the distribution of diligence skills: individuals with low diligence skills are benefiting from higher returns to social skills, while those with high diligence skills are experiencing a decline in their previously high returns to diligence skills. This may be referred to as an offsetting effect of high diligence skills on the increasing returns to social skills. Individuals with lower diligence skills experience a significant increase in the returns to social skills, which is not true for those with higher diligence skills.

Table 8 shows the changes (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 diligence, as in Figure 9. I do not find such a strong change in returns to social skills for individuals high in cognitive and diligence skills. At last, individuals with high cognitive and diligence skills experience a negative change in diligence skills returns.

I investigate this finding in Table 9. I compute the same change in returns for individuals holding a skill bundle with low cognitive skills. Table 9 illustrates a noteworthy observation: the decline in returns to diligence skills is even more pronounced among in-

[24]In Appendix 6, I show Table 30, including the results for a different skill bundle, using θ^{sc}.

Table 8: Changes (Δ) in Returns across Cohorts by Skill Bundle (High Cognitive $\theta^c > 0$)

	Changes in returns			
	$\theta^c > 0, \theta^d < 0$		$\theta^c > 0, \theta^d > 0$	
	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)
Diligence skills θ^d	0.028	0.037	-0.059**	-0.055
	(0.024)	(0.043)	(0.025)	(0.042)
Social skills θ^s	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. θ^j with $j \in J \in \{c, d, s\}$ represents cognitive, diligence, and social skills. All changes are expressed in percentage points. All confidence intervals are computed relative to $\Delta = 0$, i.e. no change across cohorts.

Table 9: Changes (Δ) in Returns across Cohorts by Skill Bundle (Low Cognitive $\theta^c < 0$)

	Changes in returns			
	$\theta^c < 0, \theta^d < 0$		$\theta^c < 0, \theta^d > 0$	
	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)
Diligence skills θ^d	-0.014	0.006	-0.098*	-0.108***
	(0.015)	(0.030)	(0.052)	(0.027)
Social skills θ^s	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. θ^j with $j \in J \in \{c, d, s\}$ represents cognitive, diligence, and social skills. All changes are expressed in percentage points. All confidence intervals are computed relative to $\Delta = 0$, i.e. no change across cohorts.

dividuals with low levels of cognitive and high levels of diligence skills. These individuals experience a significant drop by 10.8 percentage points in diligence skills returns. Individuals with low cognitive abilities but high diligence skills do not benefit from increasing returns to skills. They are more likely to find themselves in low-skilled routine jobs. Individuals with lower cognitive and diligence skills benefit considerably from the increasing returns to social skills. This leads to an overall rise in skill returns, primarily driven by the increasing returns to social skills. Additionally, the offsetting effects of high diligence skills remain consistent among individuals with low cognitive abilities.

These findings suggest that a bundle with high diligence skills may make individuals worse off. This is most likely connected to the fact that conditional on social skills, individuals high in diligence skills have a comparative advantage in performing routine tasks, as I empirically test in Section 4.1.2. This is the most important mechanism to explain the negative change in returns to diligence skills and its offsetting effects on increasing returns to social skills.

4.1.2 Occupational Sorting

The findings of previous sections largely align with the model prediction included in Acemoglu and Autor (2011). In this section, I show that individuals with higher diligence skills hold a comparative advantage in performing routine tasks. This explains why returns to diligence skills have diminished, and a bundle with higher diligence 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. Then, I re-estimate the dynamic model in Section 3 by substituting the log-hourly wage equation in the model (Equation 10) with three equations including three dummies indicating task content of each occupation above the 50 percentile. Then, I estimate the effects of a σ increase on sorting into an occupation that is task intensive in either social, routine, or cognitive. The results are included in Table 10.

Indeed, individuals with higher diligence skills have a comparative advantage in sorting into routine-intensive occupations. This generates an overall reduction in returns to diligence skills for all individuals, conditional on their bundle of skills. Therefore, we observe a large decline in wage returns to diligence skills, especially for individuals with

Table 10: 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)**
Diligence skills (θ^d)	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.

lower cognitive skills. These individuals are the most likely to sort into low cognitive, high routine occupations.

5 Robustness Checks

5.1 Task Content without Latent Factors

As a first robustness check, I estimate the task content of each occupation without relying on latent factors but using continuous measurements. Each group is associated with a task using broader groups, aggregating these into continuous measurements and then standardized. These continuous measurements are defined in Appendix, Section 6. Figure 13 in Appendix is produced with the same procedure as Figure 2, using these continuous measurements. The patterns are similar, with occupation intensive in social tasks increasing substantially over time. This is mirrored by a large decline in occupation intensive in routine tasks. The main difference relates to non-routine analytical (cognitive) task, that, using these measurements, seems to rise together with social tasks. Figure 21 replicates Figure 2 using the O*NET measures from Deming (2017). In Figure 20, included in Appendix 6, I perform again the same calculations of Figure 3, while using these continuous measurements. The results are, again, largely in line with the results of Figure 3. 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 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 wage observations for each individual. The results are included in Table 32 in the Appendix, 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 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

Table 11: Results Excluding Individuals by Year

	(1) Changes	
	Direct	Total
Cognitive skills (θ^c)	0.002	-0.039
	(0.026)	(0.029)
Diligence skills (θ^d)	0.007	-0.011
	(0.016)	(0.023)
Social skills (θ^s)	0.049**	0.070***
	(0.021)	(0.026)

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 11 in Appendix. 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 diligence skills. The results align with Figure 7.

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 set of multidimensional skills, 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 33 in Appendix, where I compute the wage return to a σ increase for cognitive and non-cognitive skills.[25] While cognitive skills positively affect 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. In comparison, the increase of 6.4 percentage points for non-cognitive skills is not statistically significant.

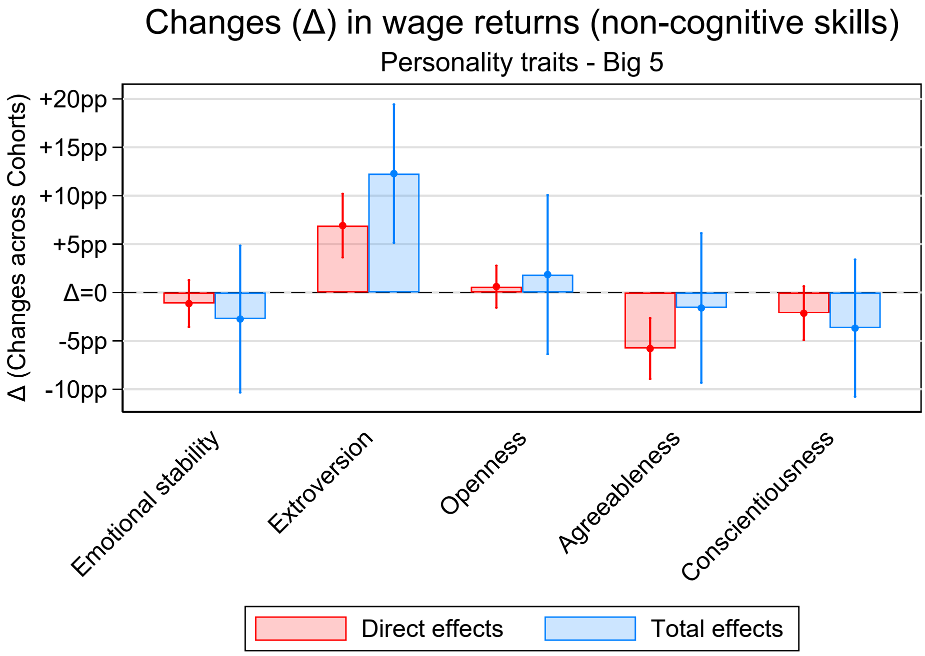
Figure 22 in Section 6 in the Appendix provides an overview of the changes in wage returns resulting from a σ increase in each cognitive skill across cohorts. When considering the total effects, verbal and math abilities have a sustained return to skills across cohorts M and Z respectively: 5.48% vs. 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%). Most changes regarding the returns on cognitive skills occurred at the labor market level, with minimal differences observed within the educational setting.

Figure 10 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 indicates social skills.[26] Relative to non-cognitive

[25] 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.

[26] The latent factor interpreted as social skills is constructed by normalizing one of the measures for

Figure 10: 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.

skills, conscientiousness is one of the personality traits mainly associated with my factor representing diligence factors. This displays a downward trend, which is not significant. Results for other diligence skills are contained in Section 6 in Appendix.

6 Conclusions

This paper develops a new dynamic model with endogenous multidimensional skills to estimate direct and indirect returns to skills, controlling for unmeasured ability differences. It analyzes which specific skills are experiencing a rising (falling) demand and, as a result, yield higher (lower) returns over time. Overall, it documents the evolution of task content of occupations and estimates changes in returns to multidimensional skills in Germany from 1984 to 2020.

This paper offers a new model to control for unmeasured ability differences and estimate direct and total returns to skills. This paper contributes substantially to the literature: this method is new relative to papers estimating returns to multidimensional

building the latent factor used in the Big 5 personality traits literature, measuring extroversion.

skills over time, such as Deming (2017) and Edin et al. (2022). This is one of the first papers to estimate direct and total returns to endogenous skills while accounting for unmeasured ability differences. These skills include one cognitive and two non-cognitive skills, social and diligence.

Moreover, following Acemoglu and Autor (2011), I link changes in returns to skills to the task content of occupations. This paper offers a novel measure of task content based on ESCO relative to the previous literature. Using a latent factor approach, I categorize occupations based on their task content in routine, social, and cognitive tasks. Employment share surged by 18 percentage points for occupations emphasizing social skills, regardless of their cognitive task content.

This paper shows a significant increase of 6.4 percentage points in the returns to social skills. This change is paired with a negative change in returns to diligence skills, driven by low cognitive individuals. High diligence skills offset higher returns to skills: I find no evidence of higher returns to social skills for individuals with high diligence skills. This result is especially true for low-cognitive individuals, indicating that low-cognitive-high-diligence, having a strong comparative advantage in routine-intensive occupations, are particularly affected by routine task displacement.

Consistent with Deming (2017) and Edin et al. (2022), this paper finds evidence supporting the growing importance of social skills in the labor market. However, this paper contributes to this literature by showing that low-cognitive individuals are worse off because of a drop in returns to diligence skills. This happens because of sorting into routine-intensive occupations. This result connects to Acemoglu and Restrepo (2022): a major part of income inequality in the U.S. can be explained by the wage decline of workers specialising in routine tasks. This result also aligns 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 higher content of social tasks. This paper also finds a significant 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.

As highlighted by Deming (2017) and Edin et al. (2022), there are promising topics to be examined on multidimensional human capital, such as the development of multidimensional skills, the impact of educational expansion on multidimensional skill mismatch, and the impact of novel technologies, such as artificial intelligence, which could replace cognitive tasks.

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Appendix 1.A: Data

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.

1.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[27] serves as a comprehensive multilingual classification system for labor markets in Europe[28]. 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 labor 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".[29]

These narrower skills are considered either essential or optional for each occupation. Therefore, the narrow skill "coordinate construction activities" is essential for occupations,

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

[28]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.

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

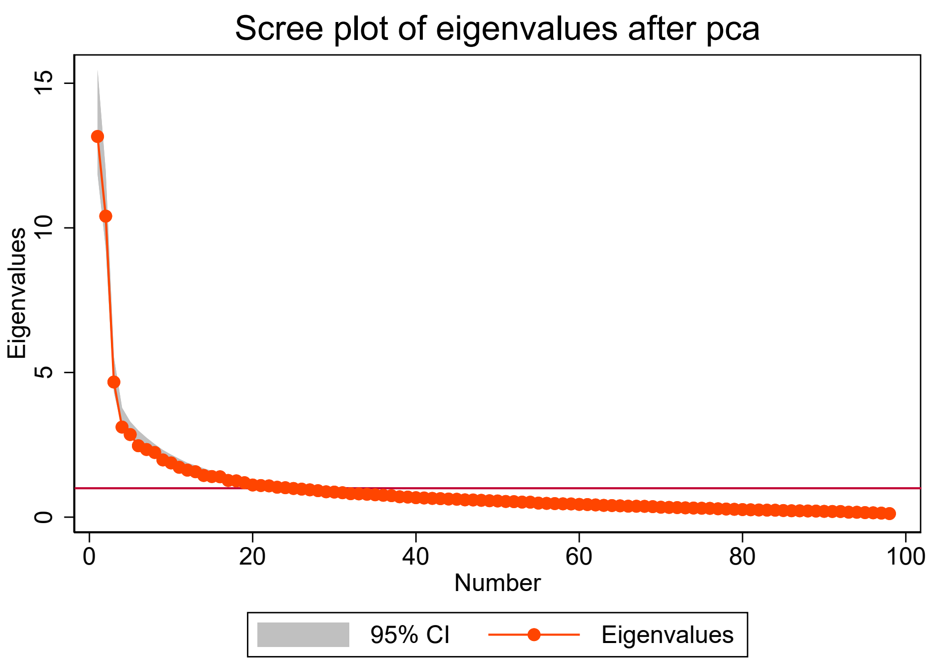
such as underwater construction supervisor, demolition supervisor, or bridge construction supervisor. I categorize each occupation using the full set of around 13'890 skills descriptions in the following way. For each occupation, I use the 2 digits (broader) skill groups and I define each occupation 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[30], I need to further reduce this dimensionality.

1.A.1.1 Measurement System for Tasks

In this section, I further reduce the dimensionality of ESCO 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 broader groups selected from ESCO. From Figure 11, it is clear that the 3 main components explain a large part of the variation, while from the 4th component, the added value is only marginal.

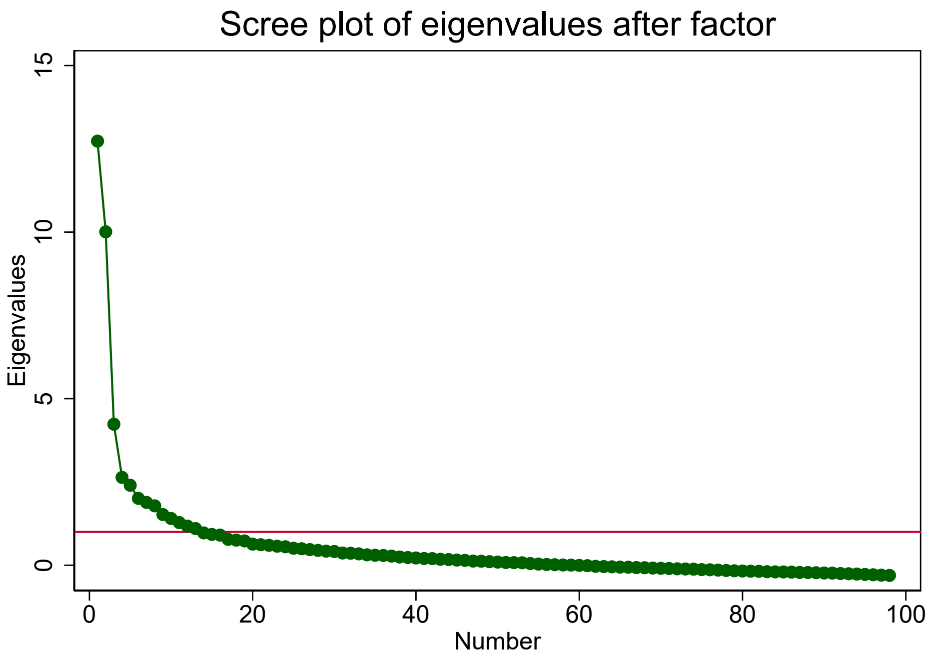
Figure 11: ESCO PCA Analysis



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

The second step consists of an Explanatory and a Confirmatory Factor Analysis (EFA and CFA). Starting with EFA, from Figure 12, the results are rather similar to the PCA, as shown in Figure 11, with three factors capturing a large part of the variation, and with only marginal value to further factors.

Figure 12: ESCO EFA Analysis



In Table 12, I show that the three main components extracted using PCA are highly correlated with the three main factors extracted using EFA.

Table 12: 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 13.

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 13: Measurement system for latent factors for task content

This is done 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):

$$m_{ij}^E = a_j + \lambda_{ji}\gamma_i^S + \lambda_{ji}\gamma_i^R + \lambda_{ji}\gamma_i^C + \varepsilon_{ij}, \tag{18}$$

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 14: 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 14, 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 strongly correlated between PCA component 1 and Factor 1, indicating a strong correlation between social and cognitive tasks (as indicated in Deming, 2017).

In Table 15, I also include the correlation between the ESCO measures and the O*NET, showing a strong positive correlation. One of the advantages of ESCO is that there is more variation, as the measures are based on ISCO-08 and it is more detailed relative to OCC1990 (as in Deming, 2017).

Table 15: Correlation between ESCO and O*NET

	Math (O*NET)	Routine (O*NET)	Social (O*NET)
Social γ^S	0.4677	-0.4214	**0.5886**
Routine γ^R	-0.1276	**0.3679**	-0.3799
Cognitive γ^C	**0.5141**	-0.0303	0.2987

1.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 16: 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 16, 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 17: 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

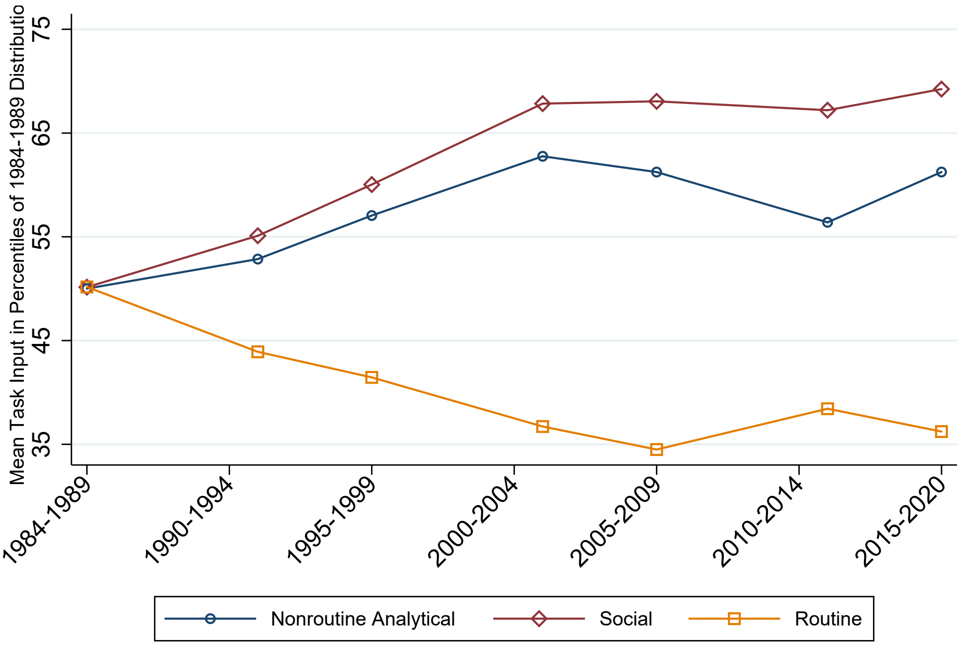
Notes: Social γ^S, Routine γ^R, and Cognitive γ^C denotes the factors extracted using the model, while Social cont., Routine cont., and Cognitive cont. denotes the continuous measures of task content, normalizing the number of narrower skills contained in each occupation.

In Table 17, 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.

1.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.

Figure 13: Worker Tasks in Germany, 1984-2020



Occupational Task Intensity based on ESCO 2020

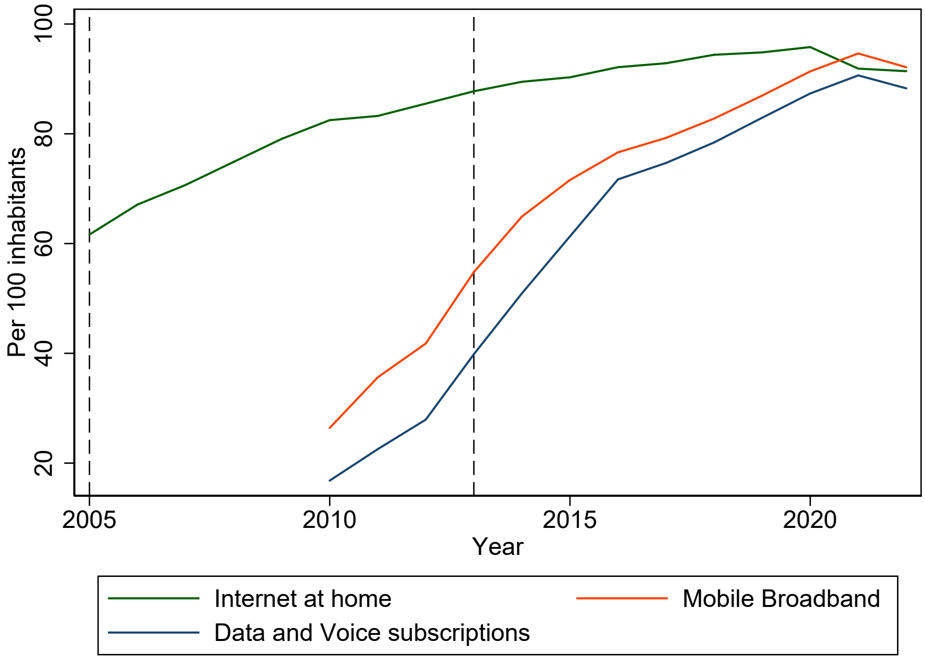
Sources: SOEP Data, divided in decades

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. It 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.[31]

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 after 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.

[31]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.

Figure 14: Internet Use across Cohorts (OECD Data)



1.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.[32]

From a practical perspective, in Table 18, 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.

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).

1.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

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

Table 18: 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	

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).[33] 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.[34] Indeed, both contain a large set of measurements aimed at identifying, with measurement error, a limited number of latent factors. Following Humphries et al. (2023), Toppeta (2022), and Deming (2017), 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,

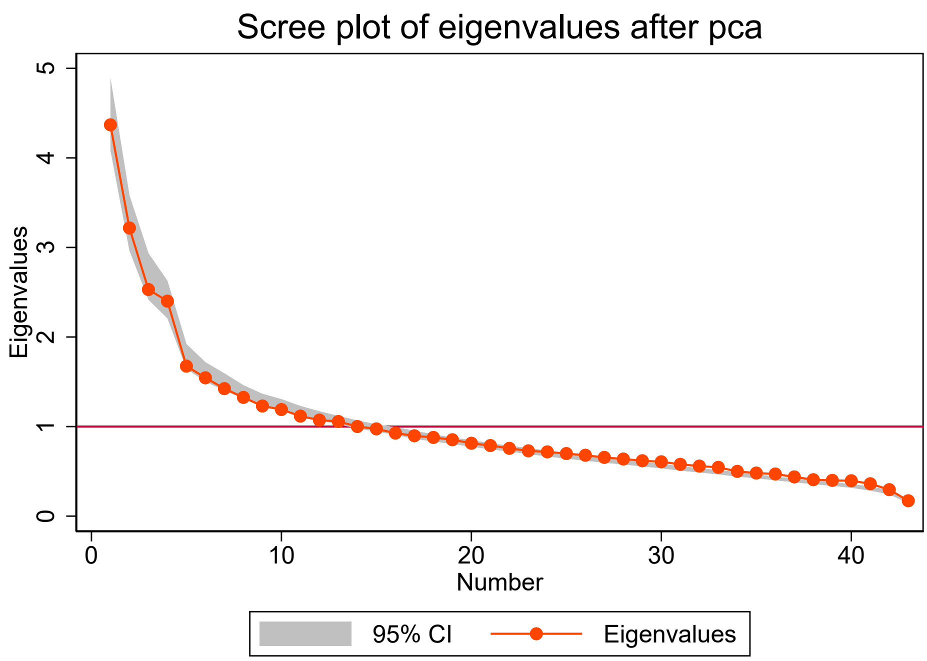
[33]To measure cognitive skills, the participants took part in a validated short version of the well-established "I-S-T 2000 R"(Amthauer et al., 2001), covering all three subsets which are verbal, numerical, and figural abilities (for details see Solga et al., 2005)

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

without wasting time.

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

Figure 15: GSOEP PCA Analysis



In Figure 15, there are at least, 4 components that explain a significant fraction of the variation in non-cognitive measures.

This is also confirmed in Figure 16, where 4 main factors are above the mean. In Table 19 shows that Factor 2 is correlated with being communicative, introducing new ideas, and being outgoing/sociable. In contrast, Factor 4 is correlated with working carefully, carrying out duties efficiently, and being considerate. Factor 1 captures a factor highly correlated with neuroticism among the Big 5: often worrying, being sad, and worrying. Factor 3 is connected to extracurricular activities for music. These latest 2 factors are not crucial in our analysis.

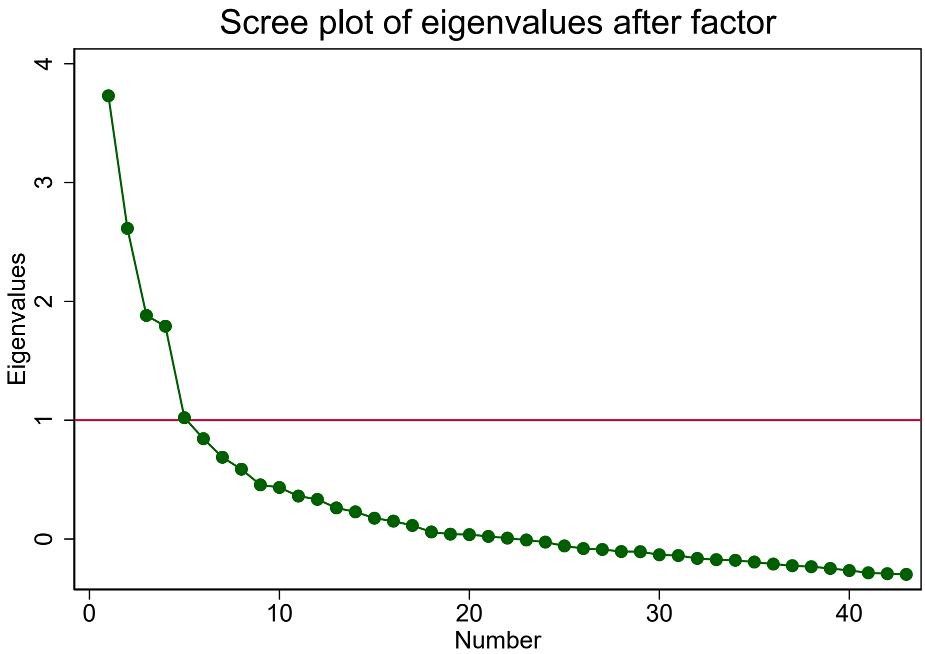
I use a measurement system with both categorical and continuous variables to measure the latent factors. The measurement system with categorical items exploits the variation from each item - instead of aggregating their responses in continuous subscales to estimate a factor model with continuous items.[35] As in Humphries and Kosse (2017), I estimate

[35]Cunha et al. (2010), Attanasio, Blundell, et al. (2020), Attanasio, Cattan, et al. (2020), and Agostinelli 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-

Table 19: EFA and Correlation with Measures

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
Personal characteristics: work carefully	-0.107			**0.698**	0.494
Personal characteristics: communicative		**0.698**		0.171	0.468
Personal characteristics: abrasive towards others	0.252	0.215		-0.233	0.834
Personal characteristics: introduce new ideas	0.114	**0.519**	0.152	0.197	0.656
Personal characteristics: often worry	**0.580**		0.143	0.153	0.616
Personal characteristics: can forgive others		0.109	0.116	0.205	0.932
Personal characteristics: am lazy	0.198			-0.522	0.681
Personal characteristics: am outgoing/sociable		**0.701**	0.112		0.483
Personal characteristics: importance of aesthetics	0.157	0.114	0.391		0.802
Personal characteristics: am nervous	0.454	-0.335	0.149		0.656
Personal characteristics: carryout duties efficiently		0.147		**0.648**	0.545
Personal characteristics: reserved	0.235	-0.557		0.106	0.622
Personal characteristics: considerate, friendly		0.155		**0.494**	0.725
Personal characteristics: lively imagination	0.184	0.284	0.233		0.830
Personal characteristics: be relaxed, no stress	-0.283	0.275		0.161	0.818
Personal characteristics: hunger for knowledge, curious		0.179	0.243	0.301	0.817
Frequency of Being Angry in the Last 4 Weeks	0.474		0.105	-0.111	0.748
Frequency of Being Worried in the Last 4 Weeks	**0.556**	-0.136	0.194		0.634
Frequency of Being Happy in the Last 4 Weeks	-0.229	0.201		0.171	0.873
Frequency of Being Sad in the Last 4 Weeks	**0.609**		0.224		0.567
Self-confidence	-0.170	0.219		0.419	0.743
Locus of control	-0.453	0.123		0.182	0.746
Class Representative		0.310	0.101	0.108	0.882
Student Body President		0.225			0.948
Involved With School Newspaper			0.181		0.957
Belong To Theatre, Dance Group		0.139	0.161		0.951
Belong To Choir, Orchestra, Music Group			**0.429**		0.816
Belong To Volunteer Sport Group		0.121		-0.127	0.960
Other Kind Of School Group			0.276		0.922
Musical Lessons Outside Of School			**0.782**		0.381
Musically Active			**0.786**		0.381
Playing sports	-0.269	0.108	0.111		0.902
Take Part In Competitions In This Sport	-0.233	0.110			0.927
Personal risk tolerance		0.378		-0.108	0.839
Opinion: Trust People	-0.316		0.222	0.195	0.812
No more reliance on anyone	0.362		-0.271	-0.103	0.782
Opinion: Distrust Strangers	0.291	0.141	-0.209		0.842
Fun today, don't think about tomorrow		0.172		-0.355	0.843
Renounce today, afford tomorrow	0.200			0.302	0.862
Political Interests			-0.336		0.870
Amount Of Closed Friends	-0.179	0.146			0.936
How Often Spend Time Steady Boy-,Girlfriend		0.184	-0.167		0.929
How Often Spend Time Best Friend	-0.102	0.187			0.954

Figure 16: GSOEP EFA Analysis



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. (2023), 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).[36]

emotional development, rather than considering the two distinct dimensions of socio-emotional skills, namely internalizing and externalizing.

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

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 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:

$$m_{ij}^c = a_j + \lambda_{ji}\theta_i^c + \varepsilon_{ij} \tag{19}$$

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

$$m_{ij}^{nc} = a_j + \lambda_{ji}^1\theta_i^d + \lambda_{ji}^2\theta_i^s + \varepsilon_{ij} \tag{20}$$

Based on this estimation, I interpret θ^{nc1} as a general measure of diligence, θ^d, such as grit, hard-working, conscientiousness, patient, while I interpret θ^{nc2} as θ^s, 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. These could be called 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^d and θ^s.[37] 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

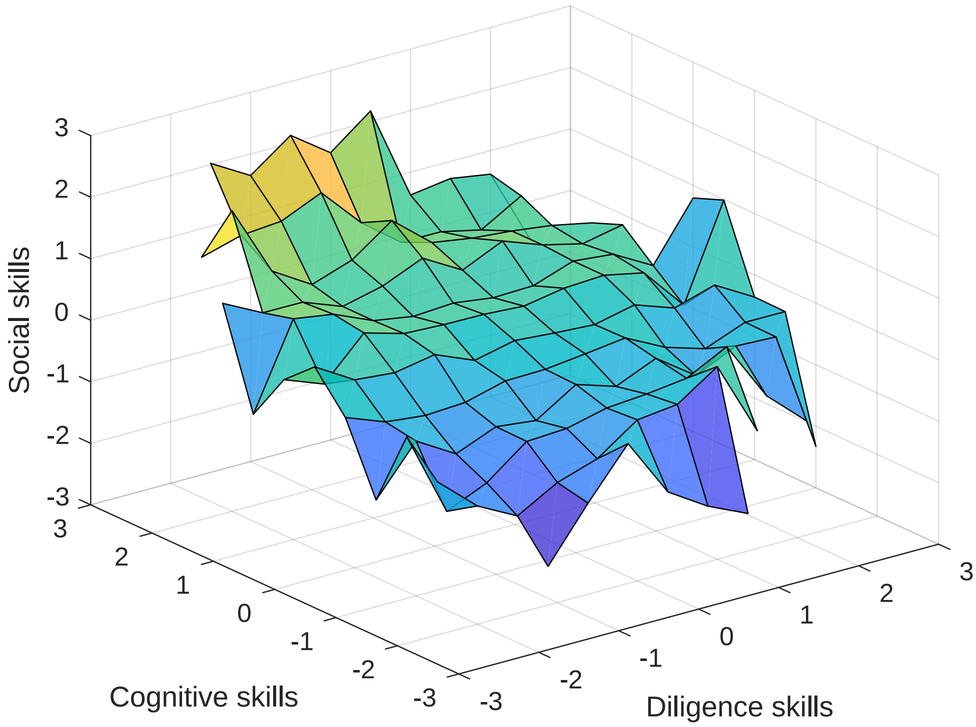
cognitive.

[37]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}. Normalizing the factor loadings to 1 and choosing dedicated measures are crucial for identifying these factors.

returns on cognitive skills at the age of 17.

Figure 17 illustrates the relationship between three multidimensional skills. It reveals that individuals with high cognitive skills but low diligence skills tend to exhibit higher social skills. Notably, social and diligence skills represent distinct dimensions of skills, and individuals may focus on developing one dimension more than the other.

Figure 17: Relationship between Skills



Notes: details on the latent factors used in this Figure are included in 6 in the Appendix. Latent factors θ are standardized to be mean 0 and standard deviation 1.

Table 20: Measurement system for latent factors θ^c, θ^d and θ^s

Measures		θ^c	θ^d	θ^s
Data on cognitive tests (COGDJ)				
20 Analogies questions	b	x		
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.[38]

In Table 23, I show the correlation between the measures of non-cognitive and social skills with the PCA and EFA measures.

Table 22: Latent factors θ^c, θ^d and θ^s and Correlation with Measures

	θ^c	θ^d	θ^s
Grade German	0.137	0.214	0.065

[38]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.

Grade Foreign Languages	0.177	0.184	0.131
Grade Mathematics	0.221	0.272	0.113
Parents Show Interest In Performance	0.118	-0.176	-0.148
Basic,Advanced Course German	-0.055	0.079	0.142
Basic,Advanced Course Mathematics	0.006	0.13	0.142
Basic,Advanced Course 1. Foreign Language	0.006	0.13	0.142
Paid Tutor	0.008	-0.029	0.039
Parents Help With Studying	0.023	0.006	0.025
Disagreements With Parents Over Studies	-0.135	-0.226	-0.147
Parents Take Part In Parents-Evening	0.111	0.115	0.06
Parents Come To Teacher Office Hours	0.063	0.102	0.191
Parents Visit Teacher Outside Office Hrs.	-0.146	-0.148	-0.043
Involved As Parents Representative	0.218	0.087	-0.02
Analogy task 1	0.292	-0.138	-0.024
Analogy task 2	0.181	0.114	-0.024
Analogy task 3	0.501	-0.01	-0.069
Analogy task 4	0.401	0.056	0.076
Analogy task 5	0.324	0.025	-0.067
Analogy task 6	0.338	0.041	-0.008
Analogy task 7	0.453	0.03	-0.104
Analogy task 8	0.244	0.034	0.009
Analogy task 9	0.405	-0.053	-0.112
Analogy task 10	0.346	0.069	0.007
Analogy task 11	0.352	0.036	-0.013
Analogy task 12	0.224	0.089	-0.018
Analogy task 13	0.201	-0.052	-0.046
Analogy task 14	0.077	0.023	-0.011
Analogy task 15	0.438	0.087	-0.002
Analogy task 16	0.118	0.017	-0.089
Analogy task 17	0.018	0	0.022
Analogy task 18	0.073	0.056	-0.037
Analogy task 19	0.24	0.089	0.134
Analogy task 20	0.162	0.049	-0.039
Task Arithmetic Operator 1	0.265	-0.096	-0.134
Task Arithmetic Operator 2	0.228	-0.02	-0.047
Task Arithmetic Operator 3	0.419	-0.111	-0.168
Task Arithmetic Operator 4	0.577	0.022	-0.015
Task Arithmetic Operator 5	0.577	-0.003	-0.091
Task Arithmetic Operator 6	0.503	0.078	-0.008

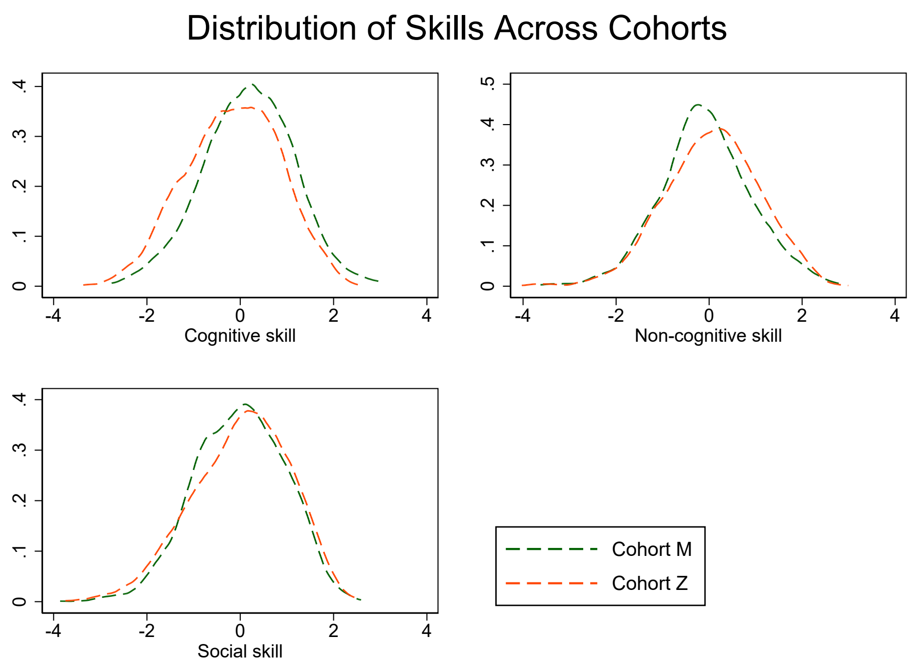
Task Arithmetic Operator 7	0.675	0.043	-0.108
Task Arithmetic Operator 8	0.51	-0.025	-0.085
Task Arithmetic Operator 9	0.463	0.061	-0.011
Task Arithmetic Operator 10	0.533	0.019	-0.019
Task Arithmetic Operator 11	0.554	0.029	-0.056
Task Arithmetic Operator 12	0.473	0.064	-0.078
Task Arithmetic Operator 13	0.544	0.085	0.016
Task Arithmetic Operator 14	0.541	-0.009	-0.175
Task Arithmetic Operator 15	0.57	0.099	-0.118
Task Arithmetic Operator 16	0.473	-0.099	-0.107
Task Arithmetic Operator 17	0.611	-0.033	-0.191
Task Arithmetic Operator 18	0.493	0.022	-0.107
Task Arithmetic Operator 19	0.468	0.069	0.03
Task Arithmetic Operator 20	0.407	0.081	0.044
Task Figures 1	0.25	-0.061	-0.116
Task Figures 2	0.243	-0.06	0.084
Task Figures 3	0.325	-0.074	-0.05
Task Figures 4	0.311	-0.053	-0.004
Task Figures 5	0.418	0.062	-0.058
Task Figures 6	0.339	0.008	-0.079
Task Figures 7	0.232	0.073	0.035
Task Figures 8	0.371	-0.037	-0.07
Task Figures 9	0.428	0.003	-0.02
Task Figures 10	0.267	-0.074	-0.082
Task Figures 11	0.262	0.09	0.244
Task Figures 12	0.247	0.055	0.079
Task Figures 13	0.206	0.078	-0.015
Task Figures 14	0.308	0.019	-0.125
Task Figures 15	0.309	0.114	-0.023
Task Figures 16	0.137	0.032	-0.029
Task Figures 17	0.281	0.015	0.01
Task Figures 18	0.096	-0.019	0.008
Task Figures 19	0.145	0.103	-0.202
Task Figures 20	0.042	0.123	-0.105
Self-confidence Factor	-0.123	0.379	0.338
Locus of Control Factor	0.119	0.333	0.095
Personal characteristics: work carefully	-0.053	0.76	0.211
Personal characteristics: communicative	-0.164	0.186	0.84
Personal characteristics: abrasive towards others	-0.084	-0.153	0.277

Personal characteristics: introduce new ideas	-0.092	0.261	0.539
Personal characteristics: often worry	-0.24	-0.104	0.11
Personal characteristics: can forgive others	-0.065	0.271	0.185
Personal characteristics: am lazy	0.107	-0.552	-0.096
Personal characteristics: am outgoing/sociable	-0.137	0.063	0.838
Personal characteristics: importance of esthetics	-0.055	0.247	0.327
Personal characteristics: am nervous	-0.122	-0.051	-0.22
Personal characteristics: carryout duties efficiently	0.048	0.775	0.248
Personal characteristics: reserved	0.061	-0.089	-0.538
Personal characteristics: considerate, friendly	-0.098	0.489	0.252
Personal characteristics: lively imagination	-0.044	0.174	0.391
Personal characteristics: be relaxed, no stress	0.1	0.325	0.391
Personal characteristics: hunger for knowledge, curious	0.172	0.441	0.4
Frequency of Being Angry in the Last 4 Weeks	-0.087	-0.237	-0.001
Frequency of Being Worried in the Last 4 Weeks	-0.087	-0.175	-0.14
Frequency of Being Happy in the Last 4 Weeks	0.044	0.318	0.421
Frequency of Being Sad in the Last 4 Weeks	-0.117	-0.218	-0.196
Class Representative	-0.045	0.247	0.351
Student Body President	-0.017	0.148	0.191
Involved With School Newspaper	0.034	0.165	0.135
Belong To Theatre, Dance Group	0.086	-0.032	0.102
Belong To Choir, Orchestra, Music Group	0.178	0.05	0.019
Belong To Volunteer Sport Group	0.032	-0.087	0.148
Other Kind Of School Group	0.002	0.138	0.078
Musical Lessons Outside Of School	0.296	0.159	0.033
Musically Active	0.283	0.186	0.114
Playing sports	0.048	0.063	0.141
Take Part In Competitions In This Sport	0.128	-0.043	0.056
Personal risk tolerance	-0.162	0.081	0.405
Opinion: Trust People	0.149	0.323	0.103
No more reliance on anyone	-0.065	-0.19	-0.011
Opinion: Distrust Strangers	-0.331	-0.095	0.21
Fun today, don't think about tomorrow	-0.073	-0.402	0.072
Renounce today, afford tomorrow	-0.09	0.257	-0.039
Political Interests	-0.137	-0.279	-0.071
Amount Of Closed Friends	0.173	0.145	0.156
How Often Spend Time Steady Boy-,Girlfriend	-0.046	0.093	0.303
How Often Spend Time Best Friend	-0.033	0.189	0.235

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 24 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.

Figure 18: Distribution of skills across cohorts



Appendix 1.B: Model

1.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

Table 21: Interpretation of Latent Factors

Big 5 questions:	θ^c	θ^d	θ^s
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

Table 23: 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
Diligence skills θ^d	0.7425	0.117	-0.6063	0.1928	-0.3365	0.1233	0.1769	0.9278
Social skills θ^s	0.7939	0.2586	0.4881	0.0976	-0.1801	0.9437	0.2263	0.2

Table 24: Correlation across skill factors

	θ^c	θ^d	θ^s
θ^c	1		
θ^d	0.1331	1	
θ^s	0.0535	0.3505	1

(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 Miller (2011), and Arcidiacono and Ellickson (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, $\pi_{k,i}$:

$$\mathcal{L}_i = \sum_{i=1}^{I} \left[\sum_{k=1}^{K} \pi_k \log \left(\prod_{t=1}^{T} \ell_{it}(\gamma_k) \right) \right], \tag{21}$$

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

$$\hat{p}_{mi} = \frac{\pi_{mi}\mathcal{L}_i}{\sum_{m=1}^{M}\pi_{mi}\mathcal{L}_i} \tag{22}$$

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.

$$\mathcal{L}_i = \sum_{i=1}^{I}\left[\sum_{m=1}^{M}\hat{p}_{mi}\log\left(\prod_{t=1}^{T}\ell_{it}(\gamma_m)\right)\right], \tag{23}$$

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.

1.B.2 Model Selection

In Table 25, I include the log-likelihood for each model by cohort and number of unobserved types, using different starting values.

Table 25: Model Selection

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

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.

1.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:

$$\log(\text{wage})_i = f_m\Bigg(X_i, \theta_i^j\Bigg) \tag{24}$$

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.[39] Therefore, this would be a stylized, yet more detailed equation of wages, relative to Equation 24:

$$\log(\text{wage}) = f\Bigg(X, f^s, \theta^j, f^e\Bigg) \tag{25}$$

Now, the returns to skills can be computed as:

$$\underbrace{\frac{d\log(\text{wage})}{d\theta^j}}_{\text{Total effect}} = \underbrace{\frac{\partial\log(\text{wage})}{\partial\theta^j}}_{\text{Direct effect}} + \underbrace{\frac{df^e}{d\theta^j}\frac{\partial\log(\text{wage})}{\partial f^e}}_{\text{Indirect effect}} \tag{26}$$

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

[39]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.

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.

1.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 6. 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.

1.B.5 Goodness of fit tables

Table 26: 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
Diligence 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

Appendix 1.C: Results

Table 27: School Recommendations and Binding Reforms

	School Enrollment S:		
	(1) Lower track enrollment	(2) Intermediate track enrollment	(3) Upper track enrollment
School Reccomendation≠S and non-Binding	-0.317***	-0.406***	-0.548***
	(0.0151)	(0.0166)	(0.0131)
School Reccomendation≠S and Binding	-0.323***	-0.373***	-0.553***
	(0.0153)	(0.0171)	(0.0136)
School Reccomendation=S and non-Binding	0.0406*	-0.0198	0.0287
	(0.0193)	(0.0197)	(0.0148)
Constant	0.422***	0.693***	0.785***
	(0.0143)	(0.0149)	(0.0110)
F Statistic	369.2***	392.5***	1306.7***
RMSE	0.335	0.460	0.416

Table 28: First-Stage: School Recommendation and School Enrollment

	(1) Lower track enrollment	(2) Intermediate track enrollment	(3) Upper track enrollment
School Recommendation: Lower track	0.342***		
	(0.0103)		
School Recommendation: Intermediate track		0.380***	
		(0.0111)	
School Recommendation: Upper track			0.566***
			(0.00905)
F Statistic	1102.1***	1166.3***	3915.2***
RMSE	0.335	0.461	0.416

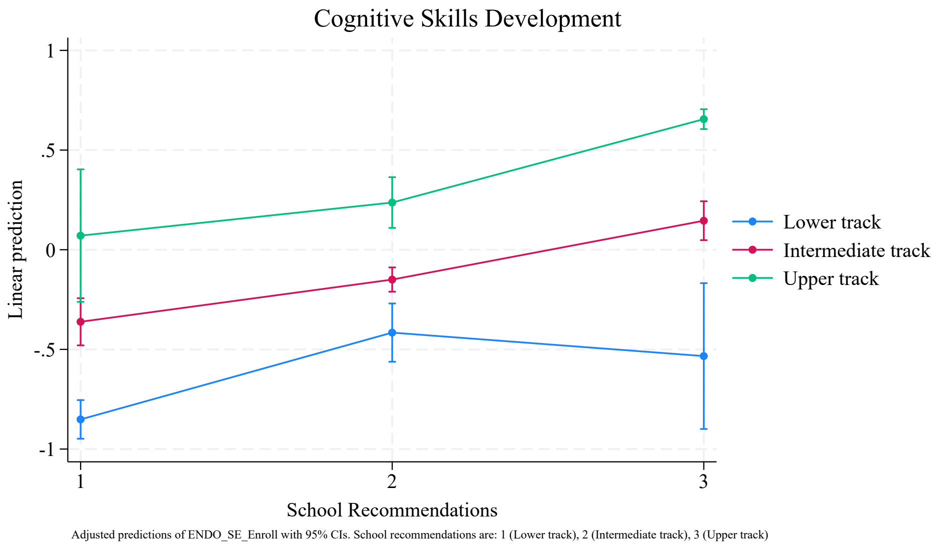


Figure 19: Cognitive Skills Development, School Recommendations and School Enrollment

Table 29: Difference between Total and Direct Returns

	(1) M (1987-1995)			(2) Z (1996-2003)		
	Direct	Total	**Difference**	Direct	Total	**Difference**
Skills	0.052	0.112**	0.060***	0.123*	0.187***	0.063**
	(0.044)	(0.046)	(0.023)	(0.063)	(0.057)	(0.025)
Cognitive skills (θ^c)	0.044**	0.105***	0.061***	0.055*	0.090***	0.035**
	(0.020)	(0.022)	(0.015)	(0.030)	(0.030)	(0.014)
Diligence skills (θ^d)	0.025	0.038	0.013	-0.017	0.007	0.024*
	(0.018)	(0.023)	(0.015)	(0.028)	(0.029)	(0.014)
Social skills (θ^s)	0.021	0.002	-0.018	0.056**	0.066**	0.010
	(0.020)	(0.025)	(0.014)	(0.027)	(0.029)	(0.012)

Table 30: Distribution of Changes Across Cohorts by Skill Bundle

		$\theta^s > 0$				$\theta^s < 0$			
		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)
	Diligence skills θ^d	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^s	-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)
	Diligence skills θ^d	-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^s	-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.

1.C.1 Changes in Complementarities

1.C.2 Model without Unobserved Heterogeneity

Table 31: 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)
Diligence skills (θ^d)	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^s)	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)
$\theta^c\theta^d$	-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)
$\theta^c\theta^s$	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)

Appendix 1.D: Robustness Checks

1.D.1 Task Content without Latent Factors

Figure 20: Relative Changes in Employment Share by Occupation Task Intensity

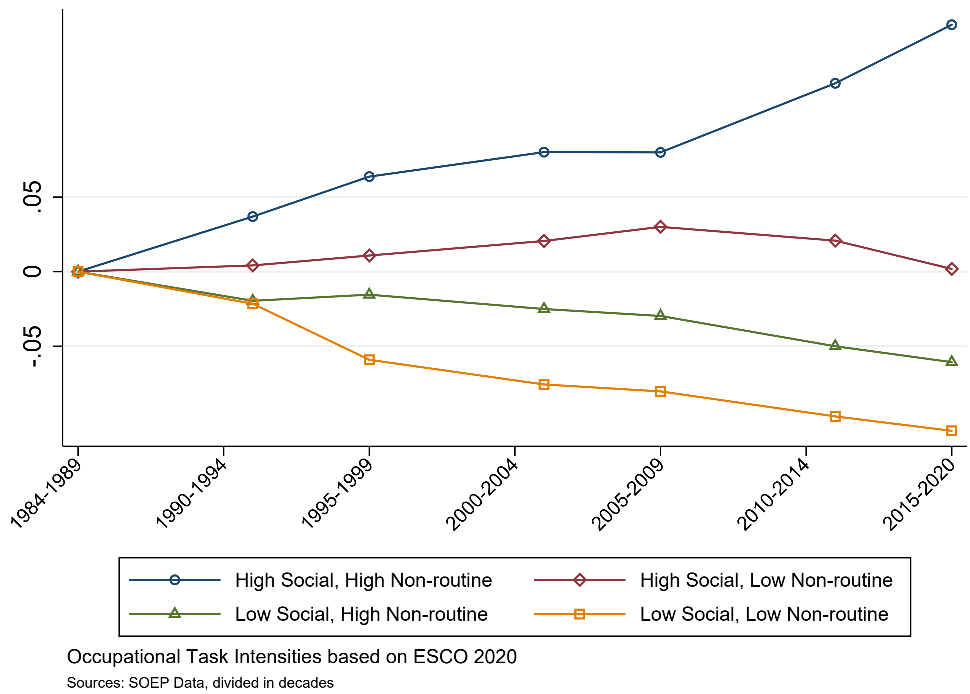
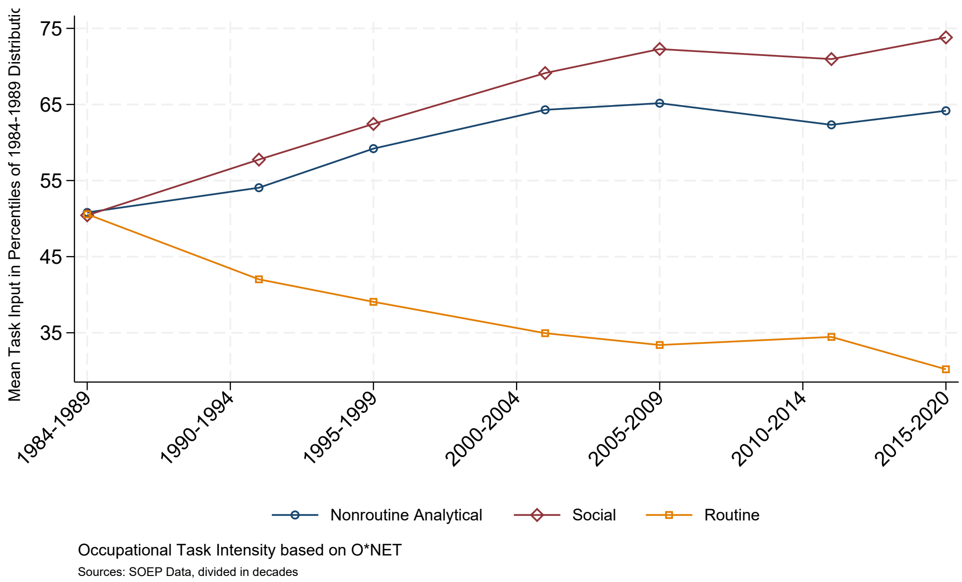


Figure 21: Worker Tasks in Germany, 1984-2020 (O*NET)



1.D.2 Changes in Present Value Earnings to Skills

Table 32: 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)
Diligence skills (θ^d)	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^s)	-0.011	-0.004	0.065	0.066	0.076	0.070
	(0.035)	(0.031)	(0.063)	(0.061)	(0.050)	(0.046)

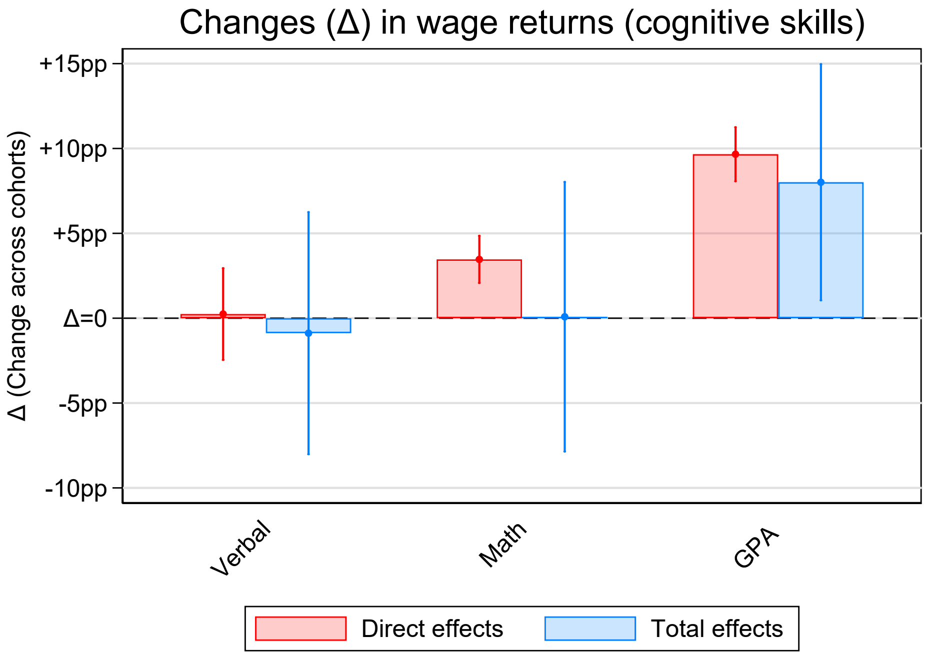
1.D.3 Changes in Returns to Multidimensional Skills

Table 33: 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).

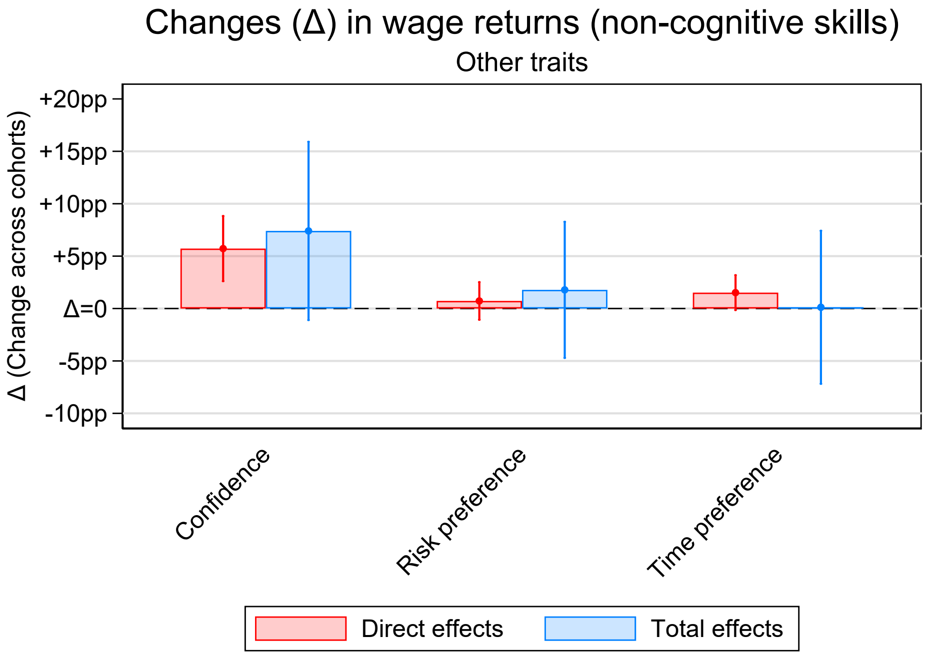
Figure 22: Changes in Wage Returns



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 23 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 23: 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.