Changes in Returns to Multidimensional Skills across Cohorts

Job Market Paper (DRAFT)

Lorenzo Navarini*

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Abstract

This paper presents an empirical investigation based on an integrated framework that incorporates technological change, tasks, and skills, building upon the recent contributions of Acemoglu and Autor (2011) and Deming (2017). The analysis begins by examining the changes in task content in Germany from 1984 to 2020 using data from GSOEP and ESCO, revealing a significant decline in routine tasks, accompanied by a substantial increase in occupations intensive in social tasks. By using a dynamic model of human capital formation, I estimate the changes in returns for a set of multidimensional skills, while accounting for endogenous skills and unobserved heterogeneity. Consistent with the theoretical framework, the findings provide evidence of increasing returns to social skills, aligning with the growing demand for occupations intensive in social tasks. However, I also find decreasing returns to non-cognitive skills, a measure of diligence, and offsetting effects of high non-cognitive skills on the increasing returns to social skills. This outcome arises due to the comparative advantage of non-cognitive skills in performing routine tasks.

Keywords: Multidimensional Skills, Return to Skills, Task Framework, Dynamic Models

*lorenzo.navarini@kuleuven.be, ECON-CEDON, Brussels Campus, LEER. This paper benefited from helpful comments at various stages from Olivier De Groote, Jo Van Biesebroeck, Christophe Bruneel-Zupanc, Dieter Verhaest, Koen Declercq, Kristof De Witte, Frank Verboven, Hannah Zillessen, Costas Meghir and several audiences at KU Leuven, UCLouvain and others. Funding for this project was generously provided by the Research Foundation Flanders (FWO) - G079420N.

1 Introduction

What is the impact of novel technologies on the labor market? How innovation changes the task content of occupations? Which specific multidimensional skills (e.g. social or cognitive skills) are impacted by technologies in terms of either substitution or complementarity effects? What are the distributional effects and implications for wage inequality? These fundamental questions have spurred extensive research in the field of economics over the past few decades (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Castex and Kogan Dechter, 2014; Beaudry et al., 2016; Deming, 2017; Autor et al., 2020; Edin et al., 2022; Humphries et al., 2022; Deming, 2023).

Indeed, in recent decades, advanced economies have undergone significant structural transformations, leading to profound shifts in the demand and supply of skills. The widespread adoption of innovative technologies, the restructuring of organizational structures due to outsourcing and globalization, as well as an unprecedented educational expansion, have all paralleled these changes. These novel technologies[1] have generated numerous consequences in the labor market, among others: (i) skill-biased technical change (SBTC), (ii) non-monotone changes in earnings and employment levels across the distribution of workers, i.e. polarization (Acemoglu and Autor, 2011; Autor and Dorn, 2013), together with a substantial shift in the demand for skills, with (iii) increasing returns to education (Castex and Kogan Dechter, 2014; Ashworth et al., 2021) and (iv) changes in the returns to multidimensional skills, favoring social skills (Deming, 2017; Edin et al., 2022; Deming, 2023).

In general, the adoption of novel technologies in recent decades has led to a growing substitution of routine tasks, consequently affecting low-skilled workers. Conversely, these technologies have complemented abstract tasks, thereby benefiting high-skilled workers (Autor et al., 2003). In a first stance, this phenomenon has been explained using the framework of skill-biased technical change (SBTC), with the literature starting from the premise that the returns to skills, as indicated by the relative wages of college graduates compared to high-school graduates, have consistently risen over several decades, despite a significant expansion in education that has led to an increase of the supply of college graduates. Consequently, the substantial increase in the supply of skilled individuals has

[1] Globalization and offshoring may be seen as the adoption of technological innovation in the organizational structure of the firm, with a potential substitution effect over both skilled and unskilled workers (Acemoglu and Autor, 2011).

been surpassed by an even greater demand for these skills. Building upon the pioneering work of Tinbergen (1974, 1975), the canonical model of the SBTC literature shows how the relative demand for skills is positively associated with advancements in technology, specifically when technical change is skill-biased. This perspective highlights that the return to skills (including a college education) is determined by a race between the growth in the labor market's supply of skills and skill-biased technical advancements. The assumption is that technological improvements naturally heighten the demand for "skilled" workers, particularly college graduates, relative to non-college workers (Goldin and Katz, 2008).

However, more recently, extensive research in economics has documented employment polarization in the United States and other OECD countries, indicating growth in both low-skilled and high-skilled occupations compared to middle-skilled occupations (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014; Akerman et al., 2015). This fundamentally contrasts with the framework of SBTC. The phenomenon of employment polarization has been linked to the declining cost of computer capital, which directly replaces workers in routine physical and information-processing tasks that are predominantly found within the middle-wage distribution (Autor et al., 2003). This phenomenon is commonly referred to as routinization, wherein occupations that heavily rely on routine tasks are being replaced by technologies that possess a comparative advantage in performing such tasks, such as computers and robots. At the same time, there is evidence suggesting that computer and information technologies (IT) complement high-skilled workers by improving their access to information (Autor et al., 2003; Beaudry et al., 2010; Michaels et al., 2014; Akerman et al., 2015).

Moreover, the majority of these papers regard the concept of skills as a single and *unidimensional* measure, i.e. college or high-school graduates. More recently, there has been an increasing number of studies highlighting the multidimensional nature of skills and human capital (Heckman et al., 2006; Deming, 2017; Humphries et al., 2022; Deming, 2023). Cognitive skills and non-cognitive skills are conceptually distinct and work together in non-obvious ways to explain significant recent trends in the wage structure (Deming, 2023). This recent literature has documented a change in the returns to multidimensional skills: while returns to cognitive skills are decreasing sharply, there is evidence of increasing returns to non-cognitive skills and to education, in the United States and other advanced economies (Castex and Kogan Dechter, 2014; Beaudry et al., 2016; Deming, 2017; Edin et al., 2020; Ashworth et al., 2021).

These novel trends, like polarization and decreasing returns to cognitive skills, could not be explained simply by using the canonical model of Tinbergen (1974, 1975). Therefore, Acemoglu and Autor (2011) and, later, Deming (2017, 2023), offered novel theoretical frameworks to understand better how these trends are linked to a more theoretical perspective.

In this paper, I present an empirical investigation based on a comprehensive framework that integrates technologies, tasks, and skills, building upon the works of Acemoglu and Autor (2011), Deming (2017), and Deming (2023). By utilizing this theoretical framework alongside previous empirical findings, my objective is to examine the changes in the tasks performed by the labor force and their connection to shifts in skill returns. Furthermore, in contrast to prior literature, I adopt a wider and multidimensional perspective on human capital, encompassing three key latent factors and recognizing each individual as possessing a diverse bundle of these features: cognitive, social, and non-cognitive skills. Within this framework, non-cognitive skills are distinct from social skills, as they encompass attributes such as hard work, diligence, and conscientiousness. In my study, the central intuition is that individuals possess a complex combination of various skills, including multidimensional dimensions of "soft" skills.

I investigate empirically this theoretical framework using data from the German Socio-Economic Panel (GSOEP) and data from the European Skills, Competences, Qualifications, and Occupations (ESCO). The GSOEP provides panel data starting from 1984, which includes a comprehensive range of standardized cognitive tests, measurements of non-cognitive skills, and other relevant characteristics. On the other hand, ESCO offers approximately 13,000 skill requirements and task descriptions for around 3,000 occupations (ISCO-08 4 digits). I can extract a set of latent factors by significantly reducing the dimensionality of the measures of skill and task, while linking ESCO to GSOEP, for estimating the task content of occupations in Germany. This allows me to derive valuable insights regarding the underlying characteristics of skills and tasks, enabling a more robust analysis within this framework.

Germany, as a prominent European country, has undergone significant transformations in its economic landscape in recent years. Analyzing data from Germany, I observe similar trends to those documented in the United States by Deming (2017), namely, an increase in the social skills task content performed by the German labor force. This shift is accompanied by a substantial decline in routine tasks, while the demand for non-routine analytical (cognitive) tasks remains relatively stable. Furthermore, there has been a notable surge in the employment demand for occupations that emphasize social skills, irrespective of their cognitive task content. These findings highlight the parallel shifts in the task composition of the German labor market and provide insights into the changing dynamics of skill demand in the country.

Moreover, I utilize a set of multidimensional skills, which measures cognitive, social, and non-cognitive skills. The latter is a measure of diligence, hard work, and conscientiousness. These are low-dimensional latent factors, which are estimated from a set of around 150 measures, included in the youth questionnaire and the cognitive test of the GSOEP. These measures include standardized tests, GPA, courses in secondary schooling, extracurricular activities, personality traits, risk and time preference, trust measures, locus of control, and other important indicators (Humphries and Kosse, 2017). To examine changes in the returns to these multidimensional skills, I utilize recent data from the GSOEP Youth questionnaire covering the period from the early 2000s to 2020. I do this using a dynamic model of joint schooling and labour market choices, while endogenizing multidimensional skill measures to previous schooling choices and performances. In this setting, I am also able to distinguish between measures of skills, as endogenous, and a measure of ability, as exogenous unobserved heterogeneity. I identify the latter using a set of exclusion restrictions, including school recommendations and school reforms in Germany over this timeframe. Moreover, using a dynamic model, I can estimate direct and total effects, heterogeneous returns to skills, dynamic complementarity, and other key treatment effects.

In line with the theoretical framework of Acemoglu and Autor (2011) and Deming (2017), I show that there is a large increase of 6.4 percentage points in the returns to social skills over this period. On the other side, there has not been any change in the returns to cognitive skills. At last, most importantly, I document a negative change of 3.1 percentage points in the returns to non-cognitive skills, conditional on both cognitive and social skills, and unobserved ability. This is largely driven by the fact that individuals with high non-cognitive skills have a comparative advantage in performing routine jobs, and, consistent with the predictions of Acemoglu and Autor (2011), the large decline in skill demand having a comparative advantage in routine tasks, also generates lower returns to skills. Moreover, high non-cognitive skills have an offsetting effect on increasing returns to skills: I find no evidence of increasing returns to social skills for individuals with high non-cognitive skills. This is especially true for low-cognitive individuals, indicating that low-cognitive, having a strong comparative advantage in routine-intensive occupations, are particularly affected by these changes. More generally, I observe a substitution from high returns to non-cognitive skills to a high return to social skills.

These findings are largely accounted for by the changes in skill demand of the German economy, considering comparative advantage and task intensity for each occupation. If the task content of routine jobs declines, individuals with a specific skill bundle, including high non-cognitive skills, who have a comparative advantage in performing these tasks, will be worse off, as predicted by Acemoglu and Autor (2011). This is also consistent with Deming (2017), where individuals with high non-cognitive skills may have a higher utility return to performing their own tasks, and, therefore, fail to benefit from increasing returns to social skills. In line with Deming (2017), I also find a strong change in returns between social and cognitive skills at the upper tail of the skill distribution, highlighting a strong complementarity between these two skill dimensions.

At last, using this model, I can take a stance on the development of multidimensional skills. I show that grade retention in secondary education, while impacting negatively both cognitive and non-cognitive skills, does impact social skills. On the other side, grade retention in primary education impact negatively all measures of skills. This means that social skills may have a different development trajectory, rather than both cognitive and non-cognitive skills.

1.1 Literature Review

My paper is intertwined with three key branches of economics: the task-based approach, multidimensional skills, and dynamic models.

Overall, there are some notable recent papers that have emphasized the close relationship between tasks and skills, while analyzing the impact of novel technologies on the labour market. Deming (2023) presents an insightful perspective that aligns closely with the empirical findings of this paper. First, Deming (2023) starts by arguing that the task framework falls short in fully explaining a range of recent trends witnessed in the United States and other advanced economies, including (i) the remarkable success of educated workers since 1980, (ii) the flattening returns to cognitive skills, and (iii) the increasing returns to non-cognitive, "higher-order" skills such as teamwork. Deming (2023) argues in favor of moving beyond a singular index view of human capital. Instead, he advocates for embracing richer, multi-dimensional frameworks to gain a better understanding of these trends. Previously, Deming (2017) and Deming (2022) have also moved in this direction by adopting a more comprehensive approach that integrates both multi-dimensional skills and a task-based framework. Lastly, Acemoglu and Autor (2011) present a simple yet powerful theoretical framework that enables a deeper understanding of the interplay between changes in tasks performed by the labour force and their implications for skill returns, from a theoretical perspective.

1.1.1 Tasks

A wealth of empirical evidence establishes a strong link between shifts in employment and wages and technological advancements, as well as the interplay between skill supply and demand (Katz and Murphy, 1992; Levy and Murnane, 1992; Bound and Johnson, 1992; Juhn et al., 1993). These findings underscore the significant influence of the widespread adoption of computer capital and robotics, which both serve as substitutes for "routine" tasks and complement high-skilled workers. Consequently, this evidence supports the notion that recent technological developments have exhibited a bias toward favoring highly skilled workers, resulting in increased employment rates and higher wages. This phenomenon is commonly referred to as the skill-biased technological change(SBTC) hypothesis.

In more recent years, additional trends have emerged that cannot be fully explained by the canonical model alone, particularly the phenomenon of polarization, characterized by non-monotonic changes in earnings levels across the income distribution (Acemoglu and Autor, 2011). The adoption of novel technologies has played a significant role in altering the tasks performed by workers, independent of shifts in industry, education, or the gender composition of the labor market. The concept of job polarization, as explored in Autor et al. (2003), is closely linked to the rapid advancements in productivity and the declining real price of information and communications technologies. This research highlights the importance of considering the specific "task content" associated with different occupations. Subsequently, a body of recent work has extended the standard model by distinguishing between skills and job tasks (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Handel, 2013). Acemoglu and Autor (2011) make a significant contribution by introducing an important extension to the canonical model that incorporates a mapping between skills and tasks. This task-based framework allows for the direct substitution of labor by technology in specific tasks, leading to possible wage declines when machines replace workers, along with non-monotonic changes in the wage structure. This represents a fundamental departure from the canonical model, which primarily focuses on technology's impact on the relative prices of high and low-skilled labor (Deming, 2023). An important implication of this framework is that technological advancements that favor one group of workers can lead to a reduction in the real wages of another group. This highlights the significant substitution possibilities between different skill groups enabled by the endogenous allocation of skills to tasks. In contrast to the canonical model, it is evident that technological change does not necessarily result in wage increases for all workers. It also makes negative effects on the real wages of the group that is being directly replaced by the machinery more likely. These same ideas can also be easily applied to the process of outsourcing and offshoring. At last, Deming (2017) shows that high-paying jobs increasingly require social skills. The skills and tasks that cannot be substituted away by automation are generally complemented by it, and social interaction has proven difficult to automate (Autor, 2015).

Previous literature has measured task content of occupation in Germany using the BIBB/IAB and BIBB/BAuA Employment Surveys on Qualification and Working Conditions (hereafter: Employment Surveys), which are representative cross-section surveys that are conducted roughly every seven years.[2] These are five survey waves (1979, 1985/86, 1991/92, 1998/99 and 2006), with each wave covering about 30,000 individuals (Koomen and Backes-Gellner, 2020). As Koomen and Backes-Gellner (2020) pointed out, the limitation of this approach is that the surveys are available until 2006 and it is a subjective measurement of task contents. In my paper, using ESCO provides a clearer and more objective way of measuring the task content of occupations. This is a major contribution of this paper, which, at this point in time, at the best of my knowledge, has not been

[2]This is a possible extension of the paper or, possibly, comparing the results obtained using ESCO and the results obtained using the employment surveys.

used.

1.1.2 Skills

In my paper, I follow the strand of literature considering human capital as a complex set of multidimensional skills, and that cannot be captured only by a unidimensional measure, i.e. college education. Moreover, in my setting, skills are endogenous to schooling and other human capital investments (Acemoglu and Autor, 2011). More specifically, I draw from recent literature documenting changes in returns to multidimensional skills. Prior literature has documented three main facts: (i) a change in the returns to both cognitive and non-cognitive skills, as a result of this structural change (Acemoglu and Autor, 2011; Beaudry et al., 2016; Castex and Dechter, 2014; Deming, 2017; and Edin et al., 2022); (ii) a change in the wage returns to education (Lundberg, 2013; Castex and Kogan Dechter, 2014; Ashworth et al., 2021). Skills are dynamic in their nature and evolve dynamically as individuals progress through their human capital formation: different educational choices have a strong impact on future skill development. As Heckman (2008) pointed out: the nature versus nurture debate is obsolete. Recent findings in epigenetics showed that the genes versus environment distinction at the origins of inequality is not clear anymore, as is the practice of additively partitioning outcomes due to "nature" and "nurture" that is common in economics. A growing literature has suggested that gene-environment interactions are essential in explaining human and animal development. Rutter (2006) provides an accessible introduction to this literature. In short hand, intelligence and abilities are not assigned at birth, but are endogenous to the child environment, the human capital formation process and they evolve dynamically. This observation is key and is at the core of my analysis. The concept of a single index model of human capital implies that the benefits of obtaining a college degree and possessing cognitive skills would exhibit a similar pattern. However, there has been a decline in the returns to cognitive skills since 2000. Castex and Kogan Dechter (2014) conducted a study using data from the National Longitudinal Survey of Youth (NLSY) 1979 and 1997 samples, enabling them to compare estimates from the 1980s and 1990s with those from the post-2000 period. An increase of one standard deviation in the Armed Forces Qualifying Test (AFQT) score was associated with a 10 percent rise in hourly wages during the 1980s and early 1990s, but only 4.5 percent during the 2000s and early 2010s. On the other hand, the economic return to obtaining a bachelor's degree increased by 6 percentage points unconditionally and by nearly 15 percentage points when accounting for cognitive skills directly in both waves (Castex and Kogan Dechter, 2014). These findings apply to all demographic groups and remain robust when considering measurement error, test time, and other factors. By utilizing test scores and administrative earnings records for approximately half of the male population in Sweden, Edin et al. (2022) demonstrated that the return to cognitive skills decreased by approximately 25 percent between 2000 and 2013. Furthermore, Beaudry et al. (2016) presented evidence that the demand for jobs requiring cognitive skills experienced a significant decline starting around 2000.

Other papers have considered multidimensional skills, using various frameworks. Many studies find positive labor market returns to measures of non-cognitive skills or personality traits (e.g. Heckman et al. 2006, Lindqvist and Vestman 2011). Other studies show evidence for varieties of human capital based on sorting patterns across jobs but do not measure them directly. Other work goes further by imposing assumptions such as different skills for blue vs. white collar occupations (e.g. Willis and Rosen 1979, Keane and Wolpin 1997, Lindenlaub 2017). Two recent papers incorporate direct measures of multiple skills into models of occupational sorting and human capital accumulation, both Guvenen et al. (2020) and Lise and Postel-Vinay (2020). These papers all provide important evidence that skills are multidimensional and that the match between worker skills and jobs is quantitatively important for wage determination. Also, Humpries et al. (2022) provide a framework that identifies latent factors as a measure of skills and incorporates them into a dynamic model. Other papers that include a latent factor of skills in a dynamic model are Heckman et al. (2006), Rodriguez et al. (2016) and Ashworth et al. (2021). Moreover, some studies examine the impact of other measures of non-cognitive skills, like personality traits. For instance, the impact of "big-five" personality traits on various outcomes, including wages, employment, education, and marriage (see Todd and Zhang, 2020). Lundberg (2013) found positive correlations between personality traits (such as conscientiousness, agreeableness, and openness to experience) and college entrance. Moreover, as highlighted by Heckman (2008), skills are endogenous to schooling and other factors. For instance, Dahmann and Anger (2014), Schurer (2017), and Kassenboehmer, Leung, and Schurer (2018) argued that educational experiences in secondary school and at university shape students' personalities.

1.1.3 Dynamic Models

At last, my paper is closely linked to the literature on dynamic models in education and labour economics, starting from the seminal papers of Cameron and Heckman (1998, 2001). To account for possible bias from unmeasured ability difference and the endogeneity of these measurements at the age of 17, I develop a dynamic model of human capital formation.

My approach is liked to the literature on dynamic treatment effects, a middle-ground between the reduced-form treatment effect and the more structural dynamic discrete choice model: while agents are presumed to make choices and account for the consequences of these choices, as is the case in a fully structural approach, we do not need to identify and model the rules driving these choices, as in a reduced-form approach (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b). Hence, while it is not possible to estimate ex-ante individual valuations or expectations, our model leaves the door open to a broader set of explanations regarding what drives these choices than just perfectly forward-looking behaviour (Heckman and Navarro, 2007; Belzil and Poinas, 2010; Heckman et al., 2018a, 2018b). Another major advantage of this approach is that it does not require us to impose assumptions on the functional forms or distribution of the unobservables (Heckman et al., 2018a, 2018b). Moreover, it enables us to decompose the treatment effects into both direct and total effects associated with later educational choices (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b). This approach has been applied and refined by, among others, Colding (2006), Belzil and Poinas (2010), Heckman et al. (2018a, 2018b), Neyt et al. (2022), Ashworth et al. (2021), De Groote (2022).

2 Data

2.1 ESCO

I investigate the changes in the task content of occupations by linking the European Skills, Competences, Qualifications and Occupations dictionary for each occupation to the GSOEP Dataset. The European Skills, Competences, Qualifications and Occupations (ESCO)[3] serves as a comprehensive multilingual classification system for labour markets in Europe. It functions as a dictionary that outlines, identifies, and categorizes professional

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

occupations and relevant skills crucial for the European Union's labor market, education, and training sectors. It is a project of the European Commission used to harmonize labour markets in 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 full 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).

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 skill groups and I define each occupation with a binary outcome if the occupation includes any of the narrower skill requirements included in the skill group. Moreover, I also use the groups for the transversal skills and competences. In this way, for each occupation, I have a set of binary outcomes, including complete information for each set of skill requirements. More specifically, each occupation is classified using a set of 101 broader skill groups. 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* (included in the ESCO website), 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".[4] These narrower skills are considered either essential or optional for each occupation. Therefore, the narrow skill "coordinate construction activities" is essential for occupations, such as underwater construction supervisor, demolition supervisor, or bridge construction supervisor.

While having reduced greatly the number of skills requirements, going from around 13'000 detailed skill requirements to 100 broader skill groups[5], I further reduce this dimensionality, as described in Section 3.1.

[4]It is possible to recover the full list at this link.
[5]It is possible to find the complete list of broader skill groups at this link.

2.2 GSOEP

I investigate the changes in wage returns to multidimensional skills using data from Germany. The analysis uses data from the 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 and Humphires and Kosse, 2016). This dataset is representative and provides a comprehensive range of socio-economic information on individuals and private households in Germany. The initial data collection began in 1984, with about 12,200 adult respondents randomly selected from West Germany. Following the German reunification in 1990, the GSOEP was expanded to include approximately 4,500 individuals from East Germany, and later, additional samples were added for further supplementation.[6] Beginning in 2000 (for individuals born in 1983), a Youth questionnaire was administered to all young people at the age of 17, which contains specific questions about education and aspirations as they are being interviewed for the first time. From 2006[7] (for those born in 1989), the questionnaire included a comprehensive set of measures, assessing both cognitive and non-cognitive abilities (see Appendix A). The GSOEP's Youth Questionnaire contains data on 9,370 individuals, which can be complemented with subsequent individual questionnaires. Overall, I have 125,728 individual-year observations for these individuals, which includes data from the household questionnaire (59,188 individual-year observations after the age of 17 and subsequent to the receipt of the Youth questionnaire) and data from the individual surveys conducted after the age of 17. Of the 9,370 individuals, data on potential cognitive performance is available for 4,055 individuals.[8] Thus, I restrict our sample to those individuals for whom I have cognitive test data, resulting in a final sample of 4,055 individuals.

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 different defini-

[6] "This instrument is used since the year 2000 and can be understood as an alternative version of the Biography Questionnaire, collecting more comprehensive information on relationships with parents, leisure-time activities, and past achievements in school, as well as on personality characteristics. In addition, there are numerous prospective questions about educational plans and plans for further training, as well as questions about expectations for future career and family."

[7] *To investigate the cognitive performance potential of adolescents, they developed a questionnaire based on the I-S-T 2000 test (Amthauer, Brocke, Liepmann & Beauducel, 2001), which is suitable for an individual panel survey.*

[8] See paneldata.org and diw.de for further information.

tions 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.[9]

In terms of observed characteristics[10], I include a set of observables following the prior literature on dynamic models:

Table 1: Exogenous variables

	(1) M mean	SD	(2) Z 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 Education	0.195	0.396	0.180	0.384
Mother 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	

I include a large set of parental background characteristics to capture potential differences in parental early schooling investment: if a parent has an upper secondary schooling diploma, has a university degree, and if holds a high-skilled occupation. I also include characteristics of the location for each individual: whether she resides in a big or middle-sized city (relative to a small city or in a rural area), and if he resides in West Germany. Skills are measured using a set of low-dimensional latent factors, including a large set of measurements on both cognitive and non-cognitive skills. This is described in Section 3.2.

2.3 German Education System

The compulsory education system in Germany covers the age range of approximately five or six years old up to 18 years old. Primary school, which typically lasts for four years (six years in Berlin and Brandenburg), provides a fundamental education in subjects such as

[9]See, for instance, Generation Z report by PEW research institute.
[10]In the model section, I will refer to these characteristics as exogenous variables.

mathematics, German language, as well as various science and social subjects. During this stage, students usually receive instruction in all main subjects from a single teacher. At the end of primary school, the schools recommend a specific type of secondary school for the students based primarily on their grades and previous performance. In some federal states, these recommendations are mandatory, meaning that students cannot easily transition to a different type of secondary school than the one recommended. However, in other states, families are not bound by these recommendations and have more freedom to choose the secondary school type for their child. Typically, students attend primary school until grade 4, and the recommendations from teachers, based on the student's prior performance, as well as parental choice, determine the allocation to different tracks. After primary school, students move on to secondary schooling. At this stage, children are assigned to one of three distinct educational paths: the basic track (*Hauptschulabschluss*), the intermediate track (*Realschulabschluss*), or the academic track, which extends until grade 13 (or 12) and leads to the university entrance qualification known as *Abitur*. The basic and intermediate tracks prepare students for vocational training or other practical forms of education. While many school models now integrate both the basic and intermediate tracks, the academic track is primarily offered by Gymnasium, a school with an academic focus. Although it is possible to switch to higher track schools, it is relatively uncommon. In 2000, only 1.5 percent of students switched to a higher track between grades 5 and 9. However, high-achieving students from lower tracks often transfer to higher tracks after successfully completing their current level of education.

3 Latent Factor and Measurement System

In this section, I describe the measurement system and the estimation of the latent factors I use for describing both tasks and skills.

3.1 Measurement System for Tasks

In Section 2.1, I have introduced ESCO, for analyzing the task content of occupation in Germany. In this paper, the main point is to reduce the dimensionality of the great number of ESCO Skill content by occupation. The high number of skill descriptions is certainly a sizeable amount of information, but it cannot be used suitably for analyzing each occupation. As I have already described in Section 2.1, I already reduce dimensionality by going from around 13'000 detailed skill requirements to around 100 broader skill groups. In Appendix A.2, there is the complete set of skill groups I use for extracting a set of latent factors.

The main point is that these skill requirements all measure an underlying factor that ranks occupations based on their skill requirements. As a modeling choice, I extract three factors from this set of measures, and I interpret them as task content relative to social, routine, and nonroutine analytical (cognitive), in line with the literature (Deming, 2017). Some jobs may present a high measure of routine tasks while having also a high degree of social task content, e.g. service jobs, as waiter or flight attendant. Other jobs may display a different set of task content bundles. The main intuition is that, by using a measurement system, we can extract a limited number of factors capturing different underlying factors measured by the task content of each occupation. This measure is used to create a bundle of skill requirements or task content by occupation, that measures the different skill requirements. In Section D.1, I document how the results are essentially stable when using continuous measures made by skill groups, without relying on the latent factors.

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 nonroutine analyticial (cognitive):

$$m_{ij}^E = a_j + \lambda_{ji}\gamma_i^S + \lambda_{ji}\gamma_i^R + \lambda_{ji}\gamma_i^C + \varepsilon_{ij} \quad (1)$$

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. After this, I link this data to the core SOEP dataset, including the full panel data. As an example, I provide Table 2, including a set of the top 10 ISCO08 occupations sorted based on each of these extracted factors. Occupations intensive in social skills are, among others: Policy administration professionals, Sports, recreation and cultural centre managers, as well as Advertising and marketing professionals. Occupations with a high content of routine tasks are, for instance: Metal working machine tool setters and operators, Mechanical engineering technicians and Assemblers not elsewhere classified. Last, occupations with high cognitive task content are, for instance: University and higher education teachers, Industrial and production engineers and Electronics engineers,

Table 2: Top 10 ISCO08 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.

3.2 Measurement System for Skills

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

Therefore, I link the questionnaire on cognitive tests (COGDJ)[11] to the youth questionnaire (JUGENDL). 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.[12] Indeed, both contain a large set of measure-

[11]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)

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

ments aimed at identifying, with measurement error, a limited number of latent factors. Following Humphries et al. (2022), Toppetta (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 Toppetta (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; Achenbach, Ivanova, Rescorla, Turner, and Althoff, 2016; Goodman, 1997, 2001; Goodman, Lamping, and Ploubidis, 2010). In line with the literature on returns to skills, following Deming (2017), I refer to them simply as a social skill (θ^{sc}) and a more general non-cognitive skill (θ^{nc}). This latter skill, therefore, is more related to diligence, the ability to focus, to be hard-working, and to work efficiently, without wasting time.

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.[13] As in Humphries and Kosse (2017), I estimate non-cognitive skills from a large set of measurements available in the GSOEP dataset: participation in extracurricular activities (including competition in sports), time allocation to a set of activities, satisfaction with school achievements, self-reported probability of future success, risk preference, time preference, trust measures, personal characteristics (Big 5), political interest, locus of control and amount of closed friends. The full list is included in Table 15. In comparison to Humphries et al. (2022), 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

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

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 5.3 for more details).[14]

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 (see Appendix B.1 for more information). For identifying θ^c, I use a set of $m^c \in M^c$ dedicated measurements:

$$m^c_{ij} = a_j + \lambda_{ji}\theta^c_i + \varepsilon_{ij} \tag{2}$$

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

$$m^{nc}_{ij} = a_j + \lambda^1_{ji}\theta^{nc1}_i + \lambda^2_{ji}\theta^{nc2}_i + \varepsilon_{ij} \tag{3}$$

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

In Appendix A.3, Table 15[15] 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

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

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

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

The latent factors are measures of the following skills, selecting the personal characteristics survey questions, used for extracting the Big 5[16]:

Table 3: Interpretation of latent factors

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

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. In Appendix A.3, Table 16 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.

In Figure 1, I show the sorting patterns for individuals with different skills. Regarding θ^c, a clear pattern emerges in the sorting of individuals into the three secondary tracks. Those in the upper track exhibit a distribution that significantly surpasses the mean. In contrast, the intermediate track aligns closely with the mean, while the lower track falls notably below the mean, in accordance with the designated characteristics of each track.

[16]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.

Regarding θ^{nc} and θ^{sc}, the sorting pattern is in line with the one observed for θ^{c}, but less strong and definite. Overall, individuals in the upper track show, on average, a larger skill dimension in all three multidimensional skills.

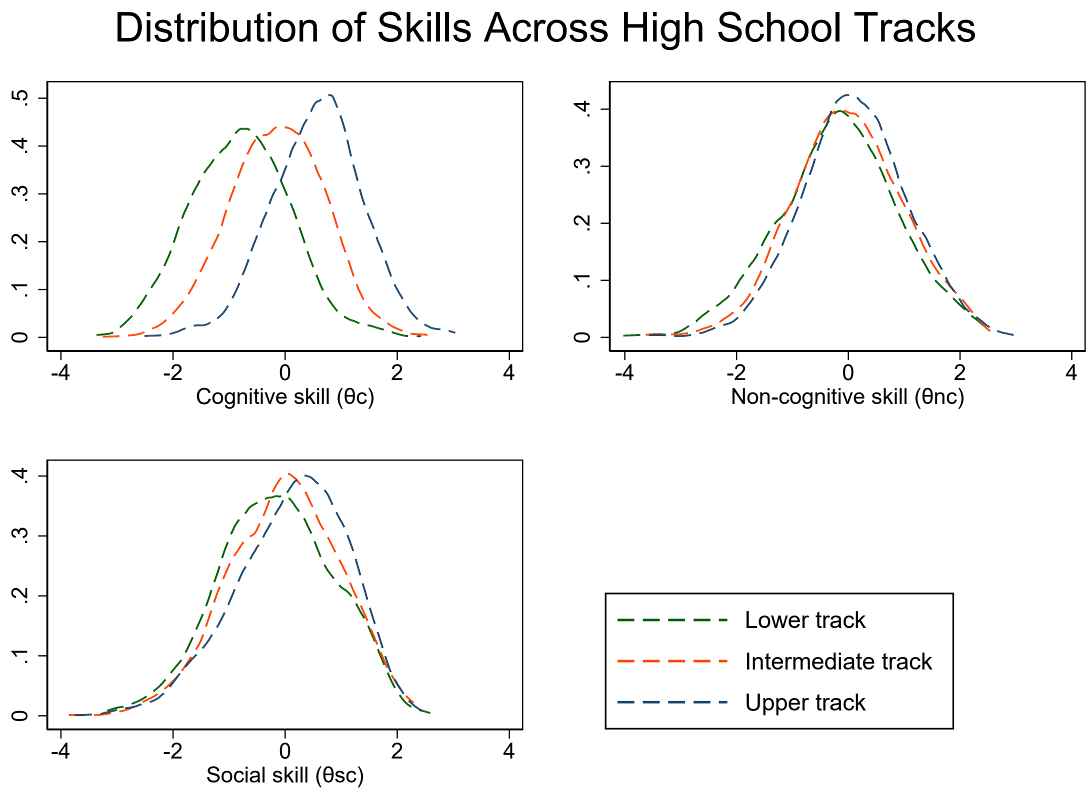


Figure 1: Distribution of Skills across High-School Tracks

In Figure 2, I show the relationship between these three different multidimensional skills. The main point, showed in Figure 2, is that individuals with high cognitive skills and lower non-cognitive skills are more likely to have higher social skills.

4 Model

This section begins by introducing a simple, yet powerful framework for estimating direct and indirect wage returns to skills, while endogenizing them to schooling choices. In this paper, I employ a dynamic model of joint educational choices and labor market outcomes to estimate them. The model is a stylized version of a dynamic discrete choice model, as developed by the dynamic treatment effects literature (see Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Ashworth et al., 2021). This is used to control for dynamic selection and unobserved heterogeneity, by considering skills and educational

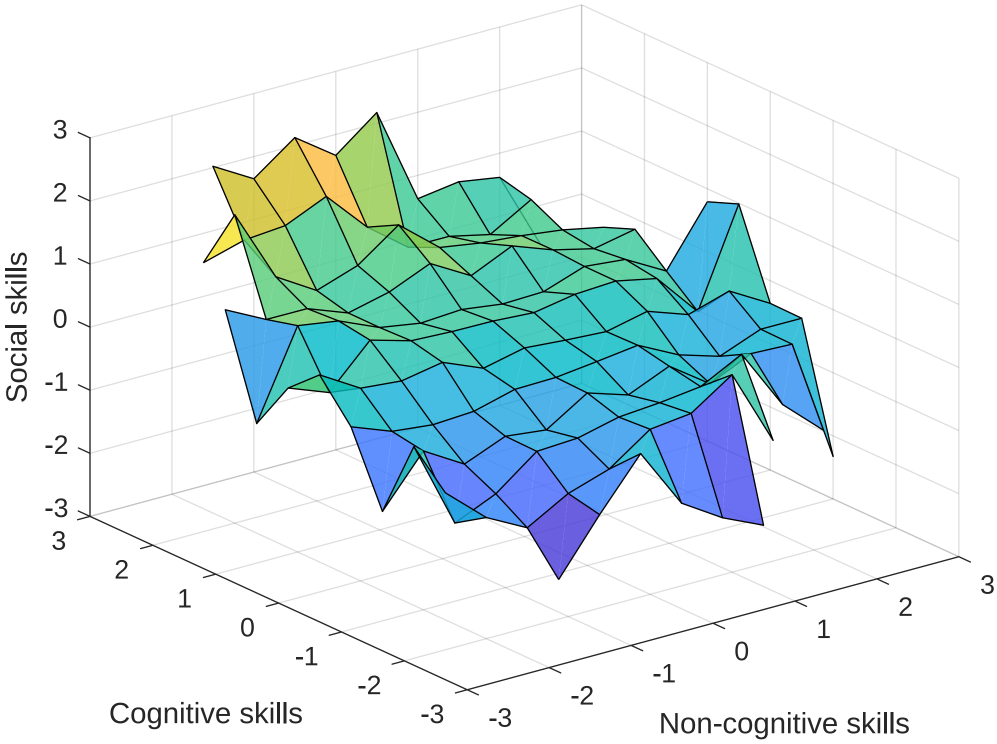


Figure 2: Relationship between Skills

choices as endogenous. Unobserved heterogeneity is identified using a set of exclusion restrictions and the panel nature of the dataset (see more in Section 4.5). The results of this model are used to perform a counterfactual analysis and identify the returns of skills on post-compulsory educational choices and labor market outcomes.

4.1 Skills and Human Capital Production

Each individual $i \in I$, member of demographic cohort d, undergoes a process of dynamic human capital accumulation. Following Ashworth et al. (2021), I estimate the model separately for each demographic cohort d.

In GSOEP, individuals in the Youth questionnaire, which I select for the model, have completed primary education and are enrolled in secondary education at the age of 17. Therefore, I observe the choices and outcomes of individuals from the age of PE_a, around the end of primary education, to the age of LM_a, when they transition into the workforce, obtain employment under a contract, and earn a starting wage. The GSOEP provides data on multidimensional skills for individuals at the age of 17. I refer to the period between PE_a and 17 as the schooling phase, and the period between 17 and LM_a as the school-to-work transition phase, as illustrated in Figure 3:

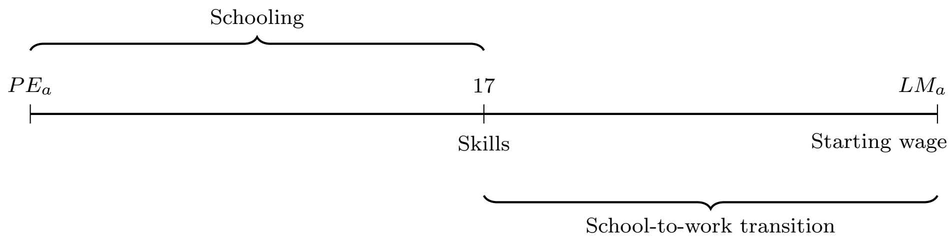


Figure 3: Stylized Model

I consider each skill, $\theta_{i,d} \in \Theta_{i,d}$, to be a function of schooling choices, $S_{i,d}$ and individual characteristics, $X_{i,d}$[17]:

$$\theta_{i,d} = f(X_{i,d}, S_{i,d}) \tag{4}$$

Once realized, skills impact both post-compulsory education choices (after the age of 17)[18] and labour market outcomes.

Starting wages are modeled as a function of individual characteristics, $X_{i,d}$, schooling choices, $S_{i,d}$, multidimensional skills, $\Theta_{i,d}$ and post-compulsory educational choices, $E_{i,d}$:

$$w_{i,d} = f\Bigg(X_{i,d}, S_{i,d}, \Theta_{i,d}(X_{i,d}, S_{i,d}), E_{i,d}(X_{i,d}, S_{i,d}, \Theta_{i,d})\Bigg) \tag{5}$$

where (5) is a stylized version of the model: both skills and post-compulsory educational choices are, also, functions of previous variables.

By utilizing the GSOEP data, we have the opportunity to incorporate a broader range of variables during both periods, enabling us to construct a model and estimate both unobserved heterogeneity and returns to skills. The key insight lies in recognizing that skills are influenced by choices made before measurement and individual characteristics, including parental background and location. This perspective aligns with contemporary findings in epigenetics, which emphasize the combined influence of genetics and the environment in shaping certain traits (Heckman, 2008). Furthermore, it is noteworthy that skills, which are realized at the age of 17, play a significant role in the decision to not drop out in secondary education, obtain a secondary diploma, and pursue enrollment and completion of tertiary education, before entering the labor market with a starting wage.

[17]In a stylized version of the model. I include also a set of other characteristics, such as local labour market conditions.

[18]This includes both secondary education last years and tertiary education choices.

4.2 Schooling Phase

In the schooling phase, individuals make a series of choices within primary and secondary education, which serve as the primary observed outcomes used to identify unobserved heterogeneity. Since unobserved heterogeneity is exogenous and present in each outcome, it can be interpreted as an individual's inherent ability (see Section 4.5).

As said in the previous section, skills are endogenous and defined by both individual characteristics, human capital investments and other factors, as described in a stylized way by Figure 4.

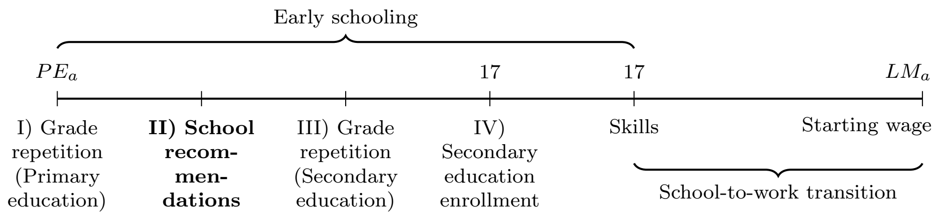


Figure 4: Model: Schooling Phase

Before starting secondary education, individuals are observed to have or not have repeated a grade in primary education. This is determined by observed and unobserved characteristics and it is the starting point of my model. 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., 2018).

At the end of primary education, also based on their observed grade repetition, individuals receive a school recommendation from schools and their teachers. Individuals may either receive a low, intermediate, or upper secondary schooling recommendation, based on their early schooling performances in primary education.[19] School recommendations are crucial in our model (see Section 2.3.), because of the exclusion restriction we impose to identify unobserved heterogeneity: school recommendations influence school track enrollment, but they do not influence later outcomes. There is a large unexplained variation among individuals who, for instance, received a lower school recommendation, but still enroll in upper schooling and manage to develop further skills.[20] In my model, unobserved heterogeneity captures this variation and it is interpreted as a source of ability

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

[20]Or attain higher educational levels and earn higher starting wages.

differential among individuals.[21] It reflects differences in factors such as grit, motivation, pure ability, and other aspects that influence both skill development and future outcomes.

I use two other sources of exogenous variation as exclusion restrictions. First, state-year variation in binding school recommendations reforms (Grewening, 2022). After starting secondary education in a given track, individuals may repeat a grade again before the age of 17 in secondary education. This aspect highlights the potential misallocation of students based on school recommendations. If teachers possess superior abilities in assessing a child's academic potential compared to parents, implementing (binding) recommendations can lead to a more effective allocation of students across various school tracks (Grewening, 2022). In a counterfactual scenario, an individual who receives a higher recommendation relative to her ability may also have a higher probability of grade repetition during secondary education. At last, in the schooling phase, individuals enroll in a track at the age of 17, before the measurement of skills. This is a function of both grade repetition variables and school recommendation. Second, I include the unemployment rate at the federal-state level for each step of the model, inducing a time-variant shock in the local labour market conditions, that may account for schooling and development choices.

$S_{i,d}$ is a set which includes $s_{i,d} \in S_{i,d}$ outcomes used for the schooling phase: grade repeated before grade 5, school recommendation at the end of primary education, grade repeated after grade 5, and school enrollment at the age of 17, as shown in Figure 4. Each $s_{i,d} \in S_{i,d}$ is a function of personal characteristics, $X_{i,d}$ [22]:

$$s_{i,d} = \beta_{s,d,0} + \beta_{s,d,X} X_{i,d} + \beta_{s,d,L} L_{i,d} + \beta_{s,d,S} S^s_{i,d} + v_{s,i,d} \tag{6}$$

where $L_{i,d}$ is local unemployment rate at federal state level and $S^s_{i,d}$ is the set of schooling outcomes realized before s.

[21] This is not the only source of identification of unobserved heterogeneity, as all outcomes are used to identify this ability differential: for instance, grade repetition and further exclusion restriction also aid the identification of unobserved heterogeneity. Unobserved heterogeneity may also be interpreted as motivation, grit, or other unobserved factors.

[22] And, therefore, environmental and parental influence on the probability of repeating a grade or underperforming in the period of primary education. This is consistent with previous literature, which finds environment, early human capital investments, and schooling choices to be fundamental in developing abilities later in life (see Heckman, 2008).

4.3 Multidimensional Skills

In my setting, each skill $\theta_{i,d} \in \Theta_{i,d}$ is endogenized into the dynamic model and it is modeled as a function of exogenous individual characteristics, $X_{i,d}$, local labour market condition, $L_{i,d}$, and a set of schooling performances, $S_{i,d}^{-SR}$[23]:

$$\theta_{i,d} = \beta_{a,d,0} + \beta_{a,d,X} X_{i,d} + \beta_{a,d,L} L_{i,d} + \beta_{a,d,S} S_{i,d}^{-SR} + v_{a,i,d} \tag{7}$$

where each skill $\theta_{i,d} \in \Theta_{i,d}$ is standardized to have mean 0 and standard deviation 1. Each skill θ, therefore, is the result of a development process that starts as early as schooling and it includes parental and other individual characteristics, which can be interpreted as the effect of the environment on skills development. Moreover, local unemployment may influence skills development as an external shock.

4.4 School-to-Work Transition Phase

Skills, as measured at the age of 17, impact both the likelihood of obtaining a specific secondary education diploma in each track (or the relative probability of dropping out) and both enrollment and completion of a tertiary education degree. Consequently, also these choices directly impact starting wages, as described in a stylized way by Figure 5.

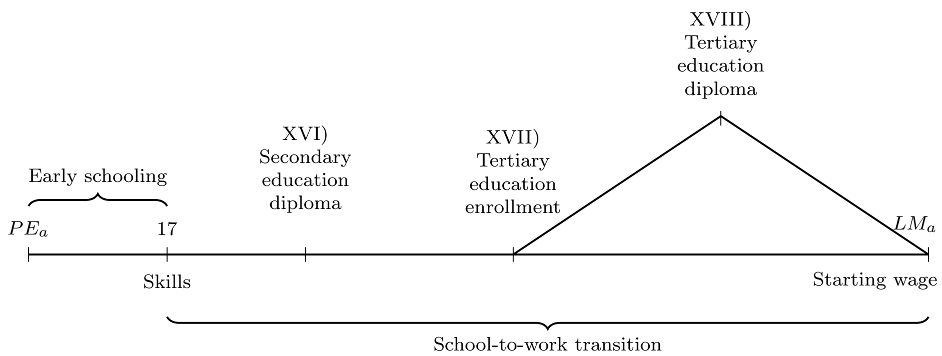


Figure 5: Model: School-to-work Transition

Higher measures of both cognitive and non-cognitive skills are correlated with higher educational attainment and better outcomes. Once abilities $\theta_{i,d} \in \Theta_{i,d}$ are realized at the age of 17, each individual i may choose which high-school diploma to obtain and, if different than lower secondary education diploma, may enroll in tertiary education

[23]Without including $s_{i,d}^{SR}$, the school recommendations included in the schooling phase set, as it acts as an exclusion restriction.

and obtain the diploma. These three choices are labelled with $e_{i,d} \in E_{i,d}$ and these are functions of individual personal characteristics, early schooling performances, and abilities:

$$e_{i,d} = \beta_{e,d,0} + \beta_{e,d,X} X_{i,d} + \beta_{e,d,S} S_{i,d} + \beta_{e,d,\Theta} g(\Theta_{i,d}) + v_{e,i,d} \tag{8}$$

where $g(\Theta_{i,d})$ includes a functional form for skills $\Theta_{i,d}$ entering the educational outcomes e function.

Log hourly wages $w_{i,d}$ at the first job after the end of education are assumed to depend on individuals characteristics, early schooling performances, abilities, and educational choices:

$$w_{i,d} = \beta_{w,d,0} + \beta_{w,d,X} X_{i,d} + \beta_{w,d,S} S_{i,d} + \beta_{w,d,\Theta} g(\Theta_{i,d}) + \beta_{w,d,E} E_{i,d} + v_{w,i,d} \tag{9}$$

I use starting log hourly wages, by removing the possible influence of endogenous work experience (Ashworth et al., 2021). This form also includes a set of skill complementarities, dynamic complementarities, and skill-unobserved heterogeneity complementarities.

4.5 Unobserved Heterogeneity and Identification

Unobserved heterogeneity is crucial in dynamic treatment effects models, because it induces correlation across different choices, addressing the issue of dynamic selection. In this literature, this is referred to as matching on unobservables, relative to matching on observables (Heckman and Navarro, 2007). In this specific setting, exogenous unobserved heterogeneity may be considered as a measure of ability, which defines a differential for individuals in developing skills and having improved schooling or labour market outcomes.[24]

I apply the following factor structure to the error term $v_{o,i,d}$:

$$v_{o,i,d} = \omega^{o}_{k,d} \eta_{k,d} + \varepsilon_{o,i,d} \tag{10}$$

in which $\eta_{k,d}$ is a random effect, independent of $\varepsilon_{o,i,d}$, and independent across individu-

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

als, and in which $\omega_{k,d}^{o}$ is an outcome-specific parameter related to this random effect. This random effect captures determinants that are unobserved and assumed to be 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 $\eta_{k,d}$ (cf. Heckman and Singer, 1984; Arcidiacono, 2004)[25]. I assume this distribution to be characterized by an a priori unknown number of K different heterogeneity types with type-specific heterogeneity parameters $\omega_{k,d}^{o}$ 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).

In order to identify unobserved heterogeneity and, therefore, identify correctly the model, I use two main strategies. First, the panel dimension of the data, specifically the autocorrelation of wages, educational choices, and wages given observed covariates, plays a crucial role in identifying the returns associated with unobserved heterogeneity. Secondly, as I have already introduced in Section 4.2, the inclusion of exclusion restrictions in the form of variables that affect choices but are not included in the subsequent outcomes is crucial for addressing the selection bias. I use a set of exclusion restrictions to identify unobserved heterogeneity, following Heckman and Navarro (2007), Heckman et al. (2016, 2018a, 2018b), and Ashworth et al. (2021). First, school recommendation is influenced by the state-year variation in binding reforms made by federal states in Germany (Grewening, 2022). For some pupils, recommendations they received 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 to do so. The effect of having either a binding or a non-binding system have an effect on how teacher recommends a track. However, this does not produce an effect on future outcomes, except through school recommendation itself. School recommendation impacts school enrollment, as in either way (binding or non-binding reforms) it will induce individuals into a specific track. However, effects on future outcomes will go through enrollment itself, with schooling recommendations to be excluded from subsequent outcomes. Lastly, as the unemployment rate at the state level is a time-variant variable, the unemployment rate related to a specific outcome acts, de facto, as an exclusion restriction for the subsequent outcomes

[25]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.

(cf. Heckman et al., 2018a, 2018b; Ashworth et al., 2021).

4.6 Likelihood Function

Without including unobserved heterogeneity, the likelihood of the model is constructed using the full set of outcomes and it is fully separable:

$$\mathcal{L}_{i,d} = S_{i,d}\Theta_{i,d}E_{i,d}W_{i,d} \tag{11}$$

$$ln(\mathcal{L}_{i,d}) = \sum_{s=1}^{S} S_{i,d} + \sum_{a=1}^{\Theta} \Theta_{i,d} + \sum_{e=1}^{E} E_{i,d} + W_{i,d} \tag{12}$$

Therefore, it can be estimated in separate stages, with consistent results.[26] However, when introducing unobserved heterogeneity, the likelihood specification becomes:

$$ln(\mathcal{L}_{i,d}) = ln\Bigg(\mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta)\Bigg) \tag{13}$$

This is not additively separable anymore and it needs to be estimated all at once.[27]

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

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

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

[27]This makes sense, as indeed, we do have a selection problem and we cannot estimate one equation, without considering the prior ones.

by the probability of being in each type k, $\pi_{k,i}$:

$$\mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta) = \sum_{i=1}^{I} \ln \left(\sum_{k=1}^{K} \pi_{k,i,d} \prod_{o=1}^{O} \mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta) \right) \tag{14}$$

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

$$\hat{p}_{k,i,d}(k|S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \pi_d) = \frac{\pi_{k,i,d}\mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta)}{\sum_{k=1}^{K} \pi_{k,i,d}\mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta)} \tag{15}$$

In the maximization step, the conditional probabilities of being heterogeneity type k 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.

$$\sum_{i=1}^{I} \sum_{k=1}^{K} \hat{p}_{k,i,d}(k|S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \pi_d) \left(\sum_{o=1}^{O} \ln(\mathcal{L}_{i,d}(S_{i,d}, \Theta_{i,d}, E_{i,d}, W_{i,d}, \omega_{k,d}; \delta)) \right) \tag{16}$$

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 k, 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, as included in Appendix Section B.1.

5 Results

In this section, I document three main findings, related to the intersection between technologies, tasks, and skills (Acemoglu and Autor, 2011; Deming, 2023). In this theoretical framework, *tasks* are units of labour that generate output (goods and services). In contrast, *skills* are a worker's endowments of capabilities for performing tasks. Workers apply their skills to tasks in exchange for wages, and skills applied to tasks produce output. The distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labor market conditions and technology.

In our setting, as explained in Section 5.3, I further differentiate between *skills*, as endogenous endowments, and *abilities*, considered exogenous and innate. Moreover, skills are considered to be multidimensional, with every individual having a bundle of cognitive, social, and non-cognitive skills.

At first, I start by using the GSOEP Core data linked with the factors extracted by the ESCO skill requirements, as explained in Section 3.2. I show that there is a large change in the German labour market from 1984 to 2020, substantially similar to the trends observed in the United States in Autor et al. (2003) and Deming (2017), and previously documented in Germany by Koomen and Backes-Gellner (2022). Therefore, I find evidence of a substantial decline in routine tasks, mirrored by a large increase in social tasks. Moreover, task intensity for non-routine analytical (cognitive) skill task measure is rather stable for the entire period. I can produce a set of hypotheses to test with a dynamic model using both the theoretical framework of Acemoglu and Autor (2011) and Deming (2017).

In the second subsection, using the GSOEP Youth questionnaire, and using the results of cohort-specific models, I can compute different counterfactual simulations and retrieve the treatment effects.[28] Therefore, I test whether the changes in skill returns are related to the large changes in task intensity and tasks performed by the German labour force. Indeed, I am documenting the changes across demographic cohorts of returns to multidimensional skills. Using the dynamic treatment effects approach, it is possible to estimate both the direct and total effects of one standard deviation (σ) increase in each multidimensional skill. Moreover, I estimate the changes in returns across cohorts for each skill θ, as included in our model specification. I can also estimate further complementarities, across skills and with unobserved heterogeneity, dynamic complementarities, and distributions of returns. At last, I also introduce heterogeneous returns to skills by observed characteristics. I link these results to the previous subsection, explaining, through Acemoglu and Autor (2011) and Deming (2017), how individuals with high non-cognitive skills have a comparative advantage in occupations with high routine task intensity. This generates a negative change in returns to non-cognitive skills and the offsetting effects in

[28]See Section B.4 for the definition of the treatment effects. See Appendix B.2 for further information on the simulations for estimating counterfactuals and the relative standard errors

increasing returns to social skills.

At last, I am documenting a set of results on the development of multidimensional skills, possible when using this model. Here, social skills are not affected by secondary school grade retention, differently from both cognitive and non-cognitive skills. This highlights how social skills may be either formed early in life or may be less affected by negative experiences in schooling and developed in other settings.

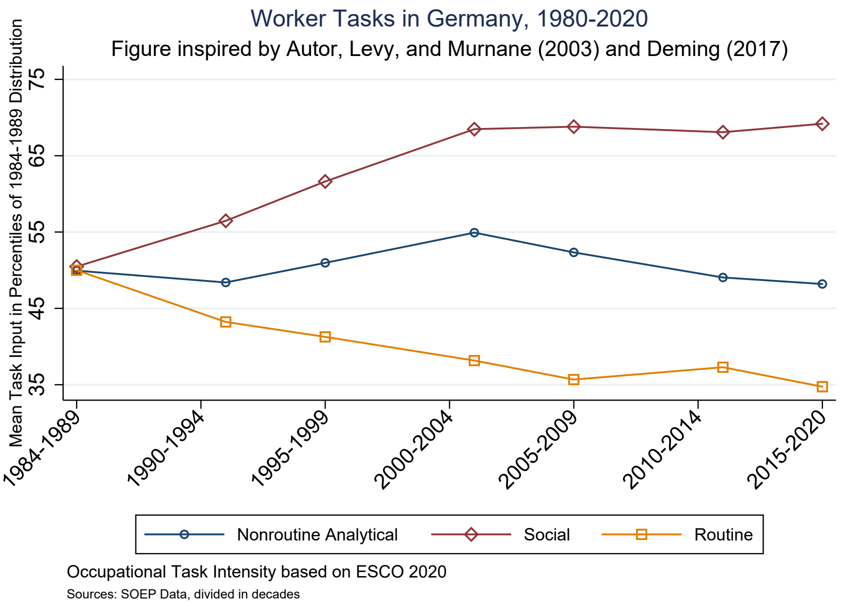
5.1 Changes in Tasks

I start by presenting the trends in the task content of occupations and relative employment growth in Germany from 1984 to 2020. Figure 6 replicates both Figure I of Autor, Levy and Murname (2003) and Figure III of Deming (2017) using data from the German SOEP and the ESCO skill requirements, as presented in Section 3.1.

At first, I consider the panel data nature of the GSOEP and select, for each half-decade from 1984 to 2020, the last observation available by individuals, so that for each half-decade I only have one observation from one single individual and the sample is still representative of the German population. Then, essentially, I follow closely the procedure of Deming (2017): each task measure variable has a mean of 50 centiles in 1984 and the data are aggregated to the industry-education-sex level, which controls for changes in task shifts in the industry and skill mix of the German economy. Subsequent movement should be interpreted as changes in the employment-weighted mean of each task relative to its importance in 1984. Relative to Deming (2017), I estimate task measures using a factor extracted from a large set of descriptions of skill and task requirements by occupations in Europe, using data from ESCO, as explained in Section 2.1 (see Section 6.1 for a robustness check using a different measure of task).

Overall, there has been a large increase in social skill-intensive occupations. Like Autor and Price (2013) and Deming (2017), I find that the labour input of routine tasks has continued to decline over this period. Routine skill task input declined by a stark -30%, comparable to the results of Deming (2017). The decline in routine tasks essentially mirrors the growing importance of social tasks in the labour force between 1984 and 2020. Moreover, I find that, despite an initial increase in the task content of nonroutine analytical (cognitive) between 1984 and the early 2000s, after 2000 this has declined and it is now at a stable level relative to 1984. Overall, this is consistent with the sharp

Figure 6: Worker Tasks in Germany, 1984-2020



Notes: Figure 6 is constructed to parallel Figure I of Autor, Levy and Murnane (2003) and Figure III of Deming (2017), but for the German economy. Task measures are factors extracted by a large set of skill requirements and task descriptions by occupation (ESCO). 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. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year.

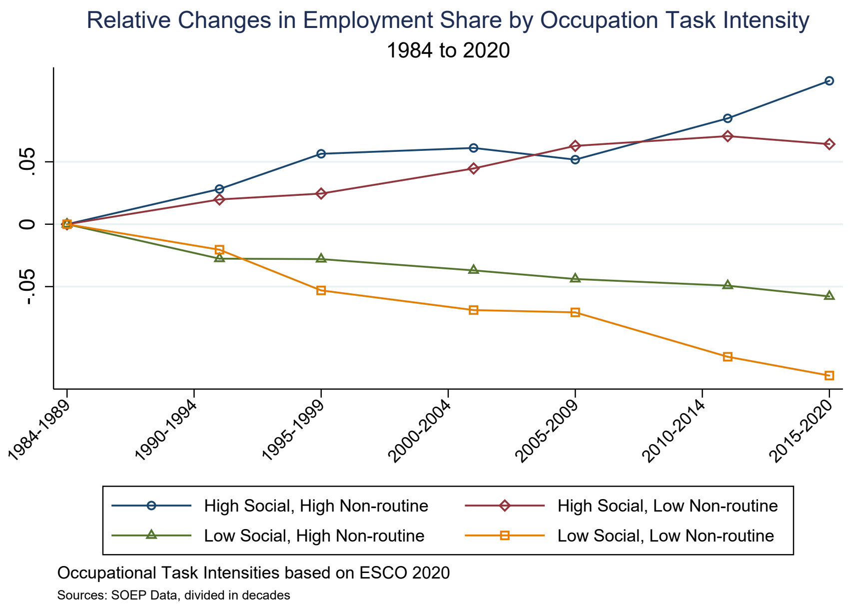
decline of nonroutine analytical (cognitive) task measures observed by Deming (2017) in the United States starting from the early 2000s.

I control for possible skill upgrading as a result of the high correlation between social and nonroutine analytical skills task measures. Following Deming (2017), I address this by dividing occupations into four mutually exclusive categories based on whether they are above or below the median percentile in both nonroutine analytical (cognitive) and social skill task intensity. I then compute the share of all labor supply-weighted employment in each category and year.

Figure 7 shows that occupations intensive in social tasks, regardless of their nonroutine analytical task content, have grown over the period. This is in line with what Deming (2017) found for the United States. Interestingly, between 1984 and 2009, there has been a convergence process, where high social, low nonroutine analytical intensive occupations have grown more relative to high social, high nonroutine occupations. However, from 2010 to 2020, this trend has reversed, with occupations intensive in high social and high nonroutine analytical growing at the fastest pace. Concurrently, there has been a large decline in employment of low social, low nonroutine intensive occupations.

By employing the theoretical framework put forth by Acemoglu and Autor (2011), it is

Figure 7: Relative Changes by Occupation Task Intensity



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 nonroutine analytical and social skill task intensity as measured by ESCO for the German economy. Source: GSOEP Data.

possible to formulate several hypotheses regarding the returns on skills by examining the observed patterns of changes in skill task measures. Notably, Acemoglu and Autor (2011) offer a prediction: if the relative market price of tasks in which a particular skill group possesses a comparative advantage decreases, 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 as a result of the shift in comparative advantage. In this setting, a large increase (decline) in the skill demand will produce a large increase (decline) in the relative market price, given the invariant supply of skill supply. Indeed, Acemoglu and Autor (2011) consider a technological change that raises the productivity of high-skill workers in all tasks, as an example. The output of the model is that some tasks formerly performed by middle-skilled workers would now be performed by high-skill workers. Relative wages paid to workers performing these (formerly) "middle-skill" tasks would actually increase since they are now performed by more productive high-skill workers. But crucially, their analysis also shows that the relative wage of medium-skill workers, who were formerly performing these tasks, would fall. In my setting, I do not consider measures of low to high-skilled workers, but I do consider workers with a multidimensional skill bundle. However, the results are intuitively similar: individuals with high social skills would have a comparative advantage in performing occupations intensive in social tasks. Indeed, considering these three task measures, we can assume that the relative market price of social tasks has increased over time, mirroring a large decline in the relative market price of routine tasks. As these tasks have become more (less) important in the labour force, there has been a greater (weaker) demand for individuals with a comparative advantage in performing these tasks. This generates increasing returns over time.

Therefore, following the predictions of the model of Acemoglu and Autor (2011), I expect a large increase in the returns to social skills, as also predicted by the model of Deming (2017). However, other skills play a role too. As the demand for non-routine analytical skill task measures has remained rather stable over the last decades, I do not expect a significant change in the returns to cognitive skills. At last, I expect a decline in the returns to non-cognitive skills, as individuals with high non-cognitive skills have a comparative advantage in performing routine tasks. This is conditional on both social and cognitive skills. As non-cognitive skills, in my setting, are a measure of diligence, not being lazy, and conscientiousness, these hypothesis is largely in line with the description of Heckman et al. (2006). Indeed, Heckman et al. (2006) write that both Bowles and Gintis (1976) and Edwards (1976) have produced a large body of evidence that employers in low-skill labor markets value docility, dependability, and persistence more than cognitive ability or independent thought. In this way, low-skilled and high-routine jobs may have strong wage returns to higher values of non-cognitive skills, as measured by my latent factor. Overall, occupations intensive in routine tasks may have a wage premium for individuals with higher non-cognitive skills.

5.2 Changes in Returns to Skills

In this section, using data from the GSOEP Youth, I estimate changes in the returns to skills across cohorts, using the model described in Section 5.3. I compare two demographic cohorts, M and Z, and the analysis focuses on estimating the direct and total effects resulting from one standard deviation (σ)[29] increase in cognitive, non-cognitive, and social skills (See the definition of these treatment effects in Appendix B.4).

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

[29] Therefore, the effect should be always interpreted as the effect of a 1 standard deviation increase of skills.

$g = total$, effect of a σ increase in each skill:

$$\Delta^{g}_{\theta^{j},d} = w_{i,d}(\theta^{j}_{i,d} + \sigma) - w_{i,d}(\theta^{j}_{i,d}) \tag{17}$$

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

Table 4: Wage returns to a σ increase in multidimensional skills

	(1) M		(2) Z	
	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)
Non-cognitive skills (θ^{nc})	0.025	0.038	-0.017	0.007
	(0.018)	(0.023)	(0.028)	(0.029)
Social skills (θ^{sc})	0.021	0.002	0.056**	0.066**
	(0.020)	(0.025)	(0.027)	(0.029)

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

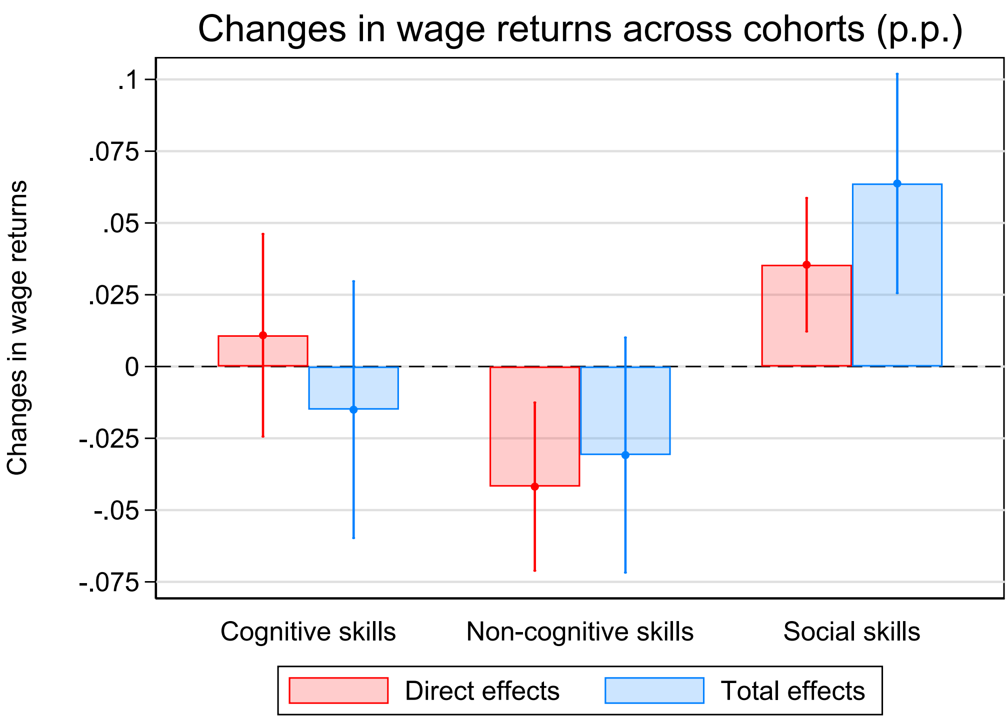
In general, I observe evidence of increasing returns to skills: from about a total (direct) return of 11.2% (5.2%) for individuals in M, I observe a total (direct) return of 18.7% (12.3%) for individuals in Z. Cognitive skills, θ^{c}, show the largest direct and total returns of, respectively: 4.4% and 10,5 % for individuals in M and 5.5% and 9% for individuals in Z. Therefore, these are stable over the most recent decades. In both cases, the indirect effect of education is substantial: 6.1% for M and 3.5% for Z. Therefore, the importance of cognitive skills is also associated with increased access to further education, with returns through this channel. The returns to non-cognitive skills, θ^{nc}, conditional on both θ^{c} and θ^{sc}, are not significant. In terms of direct effects, non-cognitive skills are associated with a 2.5% wage return for demographic cohort M, while a negative return of -1.7% is associated with demographic cohort Z. Interestingly, the returns to social skills are not significant for individuals in demographic cohort M, but become significant for individuals in demographic cohort Z: a σ increase in social skills is associated with a 6.6% increase in hourly wages for these individuals. Most of this effect is accounted for by direct effects, without taking into consideration the indirect effect of education. Therefore, this may be interpreted as a pure labour market change, as captured by the model of Deming (2017). These are total returns to education, controlling for unobserved heterogeneity, endogenous skill development and a large set of observed characteristics.

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

$$\Delta_a^g = \Delta_{a,Z}^g - \Delta_{a,M}^g \tag{18}$$

The results of this simulation are included in Figure 8. Overall, from Table 4, I observe substantial evidence indicating increasing returns to skills: the combined effect of a σ increase is associated with an 11.2% for cohort M and an 18.7% for cohort Z, with an increase of almost 7.1 percentage points across these cohorts. One of the major components driving increasing returns to skills is the higher returns to social skills, as predicted by Deming (2017).

Figure 8: Changes in wage returns to multidimensional skills across cohorts



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

Figure 8 shows the change in percentage points in wage returns to multidimensional skills across cohorts. If cognitive skills, as shown in Table 4, are stable over time and I do not find evidence of a decreased return to cognitive skills, I observe two interesting results. First, as predicted by the model of Deming (2017), the return to social skills has increased over time across these two cohorts. The return to total effects is associated with a change in 6.4 percentage points. Second, non-cognitive skills show a downward trend in wage returns, with direct effects implying a change of -4.2 percentage points for returns to a σ increase. These results are largely in line with the prediction made by the model of Acemoglu and Aturo (2011) in Section 5.1. Indeed, increasing returns to skills are driven by a large increase in returns to social skills, produced by the largest demand for individuals with a comparative advantage in performing social skill tasks. On the other side, I document decreasing returns to non-cognitive skills, which is in line with the large decline in the demand for routine skill tasks. There is no significant change in returns to cognitive skills, as also the demand for nonroutine analytical (cognitive) skill tasks has remained rather stable over time. Moreover, this model includes substantial heterogeneity and complementarities, both dynamic complementarities and skill complementarities: there are heterogenous effects of skill returns over the distribution. This is documented in Section 5.2.1.

5.2.1 Changes in Complementarities

In this section, I compute further simulations to see how complementarities between multidimensional skills have changed over time. Moreover, I can estimate changes in returns considering selected bundles of skills. Using the theoretical framework of Deming (2017), complementarities arise naturally, as individuals can be more productive and trade tasks for which they have a comparative advantage, improving substantially their productivity. Indeed, in Deming (2017), complementarities between cognitive and social skills arise because social skills become more valuable when a worker is more "productive" since she has more value to trade with her fellow worker. Also, from an empirical perspective, Weinberger (2014) finds growing complementarity between cognitive and social skills across two cohorts of young men.

From Table 5, I find evidence of increasing returns to the complementarity between cognitive and non-cognitive skills. Conditional on social skills, increasing task complexity benefits individuals with both higher cognitive and higher non-cognitive skills as they can perform tasks more efficiently, even without "trading" tasks through social skills (Deming, 2017). I fail to find increasing complementarities between social and cognitive skills, but

Table 5: Complementarities in returns to skills

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

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

this is generated by the distributional effects, as I show in Figure 9.

In Figure 9, I perform the following simulation to visualize the role of complementarities and their relative changes across cohorts. I compute the return to a σ increase in non-cognitive (θ^{nc}) and social (θ^{sc}) skills, given cognitive skills. More specifically, I compute for $j \in \{nc, sc\}$:

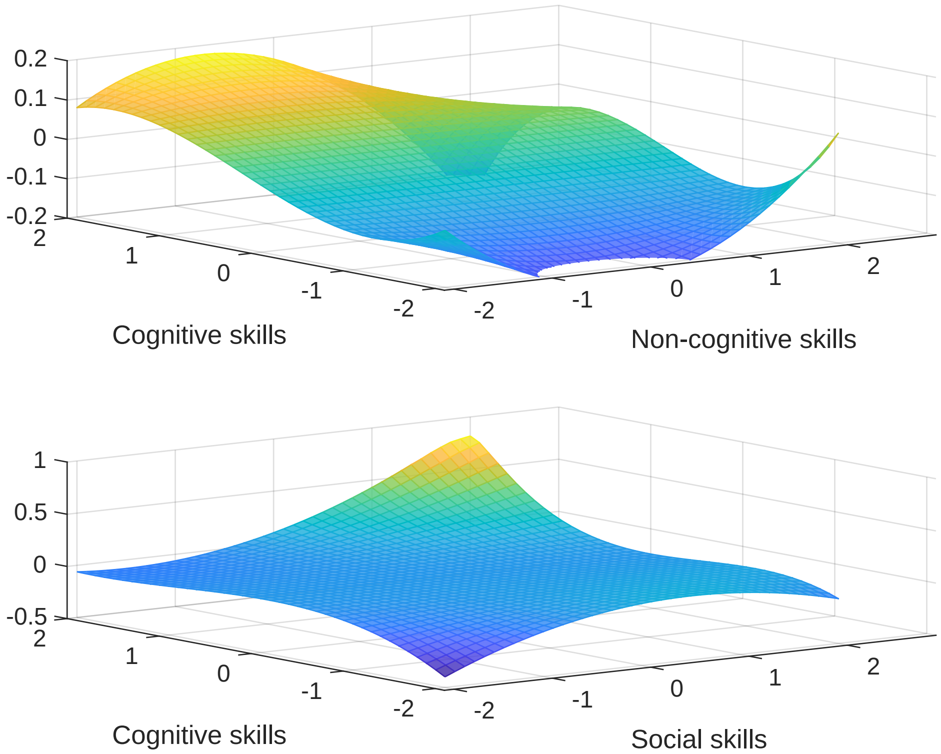
$$\Delta^{n,nn}_{\theta^j,\theta^c,\theta^{-j}} = \frac{1}{I}\sum_{i=1}^{I}\Bigg(\Big(w_{i,Z}(\theta^j_{i,Z} = nn + \sigma|\theta^c = n, \bar{\theta}^{-j}) - w_{i,Z}(\theta^j_{i,Z} = nn|\theta^c = n, \bar{\theta}^{-j})\Big) - \Big(w_{i,M}(\theta^j_{i,M} = nn + \sigma|\theta^c = n, \bar{\theta}^{-j}) - w_{i,M}(\theta^j_{i,Z} = nn|\theta^c = n, \bar{\theta}^{-j})\Big)\Bigg) \tag{19}$$

where both n and nn are vectors going from -2 to 2. In this formula, θ^{-j} represents the remaining skill, when considering θ^j (e.g. in the computation for θ^{nc}, $\theta^{-j} = \theta^{sc}$). The output is a matrix[30], which can be represented in a 3D graph, as in Figure 9.

Figure 9 shows two interesting results. First, as highlighted by the model in Deming (2017), there is a strong increase in complementarities when job task complexity increases, as individuals who are more productive in both skills are also more able to trade tasks and be even more productive. Even if I fail to find significant results when considering the average treatment effect, it is clear that this is driven by the fact the increasing returns on one side are essentially canceled out from the other side, individuals with both low cognitive and social skills. This is evident from Figure 9, where the largest changes in the returns to θ^{sc}, are concentrated among θ^c and θ^{sc} above the mean. This is the complemen-

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

Figure 9: Distribution of changes in wage returns to a σ increase across cohorts



Notes: This graph is the result of a simulation for which we compute the 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.

tarity between cognitive and social skills highlighted by the model presented in Deming (2017). Second, increasing complementarity between cognitive and non-cognitive skills is concentrated on the left side of the non-cognitive skill distribution. This means that individuals with high non-cognitive endowments do not benefit from increasing returns to skills. The more diligent an individual is, the more productive loss would come from performing too many skills. As I have shown in Figure 2, individuals with lower non-cognitive skills and higher cognitive skills are the ones with the largest social skills in the data. Conditional on having higher cognitive skills, individuals with greater non-cognitive skills do not benefit from increasing task complexity, as they have a preference for performing their own tasks over trading them. On the other hand, individuals with lower non-cognitive skills benefit the most from increasing task complexity: given increasing task complexity, these individuals may benefit from the increased capability of performing their own tasks efficiently, but with a higher propensity to trade them. This is clear from Figure 9, where the largest change in returns is concentrated between individuals with cognitive skills larger than 1σ and for individuals with non-cognitive skills comprised between -2σ and 0. The strongest change in returns is associated with high-skilled cognitive individuals but with non-cognitive skills below the mean. This mechanism could also be explained by Acemoglu and Autor (2011), as individuals who have a comparative advantage in routine tasks (high non-cognitive skills), essentially experience declining returns regardless of where they sort, as they have a comparative advantage to perform a set of tasks, which are declining.

This result highlights the importance of accounting for both non-cognitive and social skills in the analysis of the impact of increasing work complexity and technological advancements. In Table 6, I show the heterogeneity in returns to a σ increase in each skill, by considering different bundles of skills.[31]

For simplicity, I start by showing the returns to skills for individuals with a specific bundle including different set of cognitive and non-cognitive skills (Table 19 in Appendix C.1 includes the results including a different set of cognitive and social skills). In this table, I estimate the returns to a σ increase in each skill, considering heterogeneous returns by skill bundle. Notably, the analysis reveals a substitution effect occurring within the distribution of non-cognitive skills: individuals with low non-cognitive skills are benefiting

[31] In Appendix C.1, I show Table 19, including the results for a different skill bundle, using θ^{sc}.

Table 6: Distribution of Changes Across Cohorts by Skill Bundle

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

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

from the increasing returns to social skills, while those with high non-cognitive skills are experiencing a decline in their previously high returns to non-cognitive skills.

Table 7: Distribution of Changes Across Cohorts

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

Notes: This graph is the result of a simulation for which we compute the 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.

This may be referred to as an offsetting effect of high non-cognitive skills on the increasing returns to social skills. Individuals with lower non-cognitive skills experience a large increase in the returns to social skills, while this is not true for individuals with higher non-cognitive skills. On the opposite, these were individuals experiencing stronger benefits from higher non-cognitive skills and this return has disappeared.

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

Table 8: Distribution of Changes Across Cohorts

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

Notes: This graph is the result of a simulation for which we compute the 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.

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

Overall, these findings suggest that a bundle with higher non-cognitive skills may not be associated with increasing returns to skills. This is most likely connected to the fact that conditional on social skills, individuals high in non-cognitive skills have a comparative advantage in performing routine tasks, as I empirically investigate in Section 5.2.2. This is the most important mechanism I offer to explain the negative change in returns to non-cognitive skills and its offsetting effects on increasing returns to social skills.

5.2.2 Occupational Sorting

The findings of previous sections are largely in line with the prediction of the model included in Acemoglu and Autor (2011). In this section, I show that, effectively, non-cognitive skills have a comparative advantage in performing routine tasks. This explains why returns to non-cognitive skills have diminished and a bundle with higher non-cognitive skills has an offsetting effect on increasing returns to skills.

Using the task measures extracted from ESCO, I categorize each occupation with a binary variable indicating if it has a task content above the 50 percentile. Therefore, I estimate a single dynamic model, by estimating the effects of a σ increase for a higher probability of sorting into an occupation that is task intensive in either social, routine, or cognitive. The results are included in Table 9.

Table 9: Occupational sorting (Tasks and Skills)

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

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

Indeed, as I argue before, individuals with high non-cognitive skills have a large comparative advantage in performing routine tasks. A σ increase in non-cognitive skills generates a greater sorting into occupation intensive in routine tasks, while this is not evidenced for other skills. This generates an overall reduction in returns to non-cognitive skills for all individuals, conditional on their bundle of skills. Therefore, we observe a large decline in wage returns to non-cognitive skills, especially for individuals with lower cognitive skills. Moreover, I observe an offsetting effect of non-cognitive skills on increasing returns to social skills: individuals with high non-cognitive skills do not experience an increasing return to these skills. This can be explained using the theoretical framework of Acemoglu and Autor (2011). Notably, while factor-augmenting technical progress always increases all wages in the canonical model, it can reduce the wages of certain groups in this more general model. Moreover, other forms of technical change, in particular the introduction of new technologies replacing workers in certain tasks, have richer but still intuitive effects on earnings distribution and employment patterns. If the relative market price of the tasks in which a skill group holds comparative advantage declines, the relative wage of that skill group should also decline—even if the group reallocates its labor to a different set of tasks (i.e., due to the change in its comparative advantage).

5.3 Development of Multidimensional Skills

In this section, using the dynamic model of Section , I can estimate the returns to early schooling in terms of skill development. Indeed, Deming (2017) is silent about the topic of skill development and it is clear, from Deming (2022) and Deming (2023), that skill development for both θ^{nc} and θ^{sc} is a crucial topic of further research, as it is not clear where are these skills influenced and what can policy do for this. Especially now, that there is mounting evidence of increasing returns to skills. A growing body of work emphasizes the importance of "non-cognitive" or "soft" skills like patience, self-control, conscientiousness, teamwork, and critical thinking.

Using my model, I can estimate a simple treatment effect for various early schooling outcomes on skills.

In Table 10, I estimate the treatment effects associated with grade retention in both primary and secondary education for both cohorts. In both cases, grade retention in primary and secondary education implies a large loss in both cognitive and non-cognitive skills: for demographic cohort M, respectively, 52% (26%) of a standard deviation for primary (secondary) education, while a 20% (41%) of an SD for primary (secondary) education. This is in line also with the results for demographic cohort Z: 80% (22%) of a standard deviation for primary (secondary) education for cognitive skills, while a

Table 10: Development of Multidimensional Skills

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

40% (23%) of an SD for primary (secondary) education for non-cognitive skills. The evidence on social skills is different. Grade retention in primary education generates a loss in social skills in both cohorts of around 18% of a σ and 31% of a σ. However, grade retention in secondary education does not generate any significant effect on social skills: for demographic cohort M the effect is close to zero, while for cohort Z, the effect is positive but insignificant.

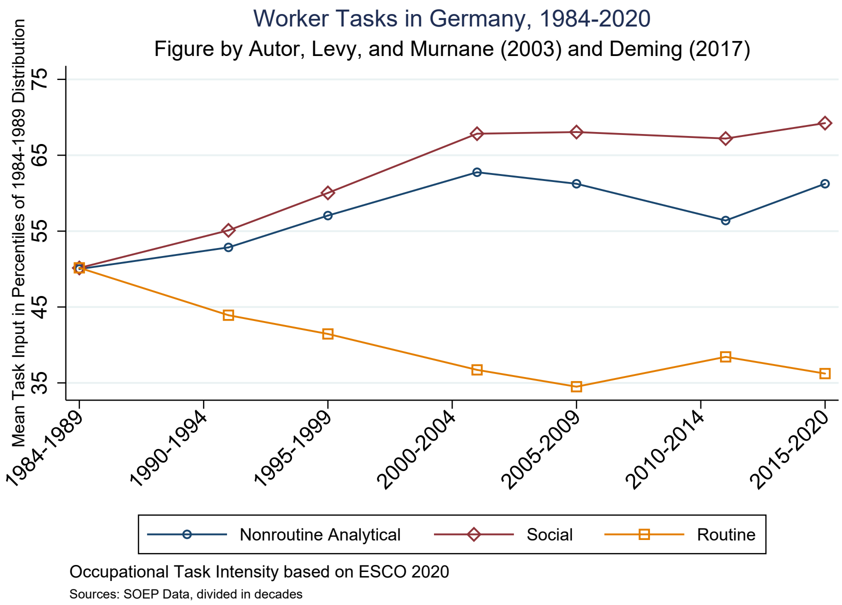
6 Robustness Checks

6.1 Task Content without Latent Factors

As a first robustness check, in this subsection, I estimate differently the task content of each occupation without relying on latent factors but using dedicated continuous measurements. Each skill group is associated with a task by using broader skill groups and these are aggregated into continuous measurements (then, standardized) used for defining each occupation. The definition of these continuous measurements is included in Appendix, Section D.1. Figure 10 is produced with the same procedure of Figure 6, but using this continous measurement and without relying on identified latent factors.

Overall, the patterns are very similar, with occupation intensive in social skills increasing substantially over the period. On the other side, this is mirrored by a large decline in occupation intensive in routine tasks. The main difference relates to nonroutine analytical task, that, using these measurements, seems to rise together with social tasks. In Figure 15, included in Appendix D.1, I perform again the same calculations of Figure 7,

Figure 10: Worker Tasks in Germany, 1984-2020



while using these continous measurements. The results are, again, largely in line with the results of Figure 7. The only difference lies in the overall decline over the last half-decades for occupation intensive in social and nonroutine tasks.

6.2 Changes in Present Value Earnings to Skills

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

Table 11: Results using Average Present Value for Earnings

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

The results are included in Table 11, with both direct and total returns from a σ increase in each skill and changes in percentage points across cohorts for each skill. The results are noisier, in terms of precision, but they indicate similar conclusions, with an increase of around 7 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 for each individual the same number of years after the starting wage.

6.3 Excluding Individuals by Year

Table 12: Results Excluding Individuals by Year

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

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 excluding individuals from the years that fall on the boundaries of the demographic cohort definition. Therefore, I exclude individuals born in 1994, 1995, and 1996. Afterward, I re-estimate the model and analyze the outcomes, as presented in Table 12.

Table 12 shows again a large increase in the returns to social skills, estimated to be around 7 percentage points for the total returns. Overall, there are not sizeable changes for both cognitive and non-cognitive skills. However, the results are in line with Figure 8.

6.4 Changes in Returns to Multidimensional Skills

In this section of robustness checks, I estimate a model without using latent factors, but by including a large set of multidimensional abilities, such as the big 5 personality traits and other dimensions. This is a similar approach to what I perform for task content in Section 6.1. I begin with Table 13, where I compute the wage return to a σ increase for cognitive and non-cognitive skills.[32]

Table 13: Changes in Returns to Multidimensional Skills Across Cohorts

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

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

While cognitive skills exhibit a clearly positive effect on both direct and total effects, the impact of non-cognitive skills is less evident.

The findings indicate that, for cohort M, a significant portion of the benefits resulting from a σ increase in cognitive skills is attributed to the indirect effect, specifically educational returns, as it is evident from the benchmark using latent factors. In contrast, in cohort Z, the majority of the return arises from direct effects. Total effects encompass both the direct effects of skills and the indirect effects through education. Specifically, 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 favoring non-cognitive skills over cognitive skills.

On the other hand, when considering the change in direct effects without accounting for the impact of education, a strong increase of 13.4 percentage points is observed for cognitive skills, while the increase of 6.4 percentage points for non-cognitive skills is not statistically significant.

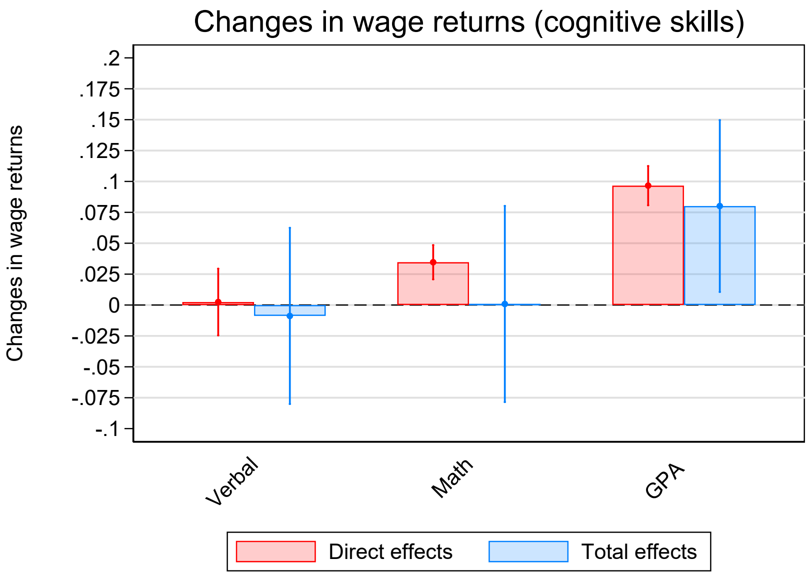
6.4.1 Changes in Returns to Cognitive

Using this model, it becomes feasible to estimate the wage return associated with one standard deviation (σ) increase in each of the distinct measures of cognitive skills. Figure

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

11[33] provides an overview of the changes in wage returns resulting from a σ increase in each cognitive skill across cohorts. The depicted changes encompass both the direct and total effects.

Figure 11: Changes in wage returns



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

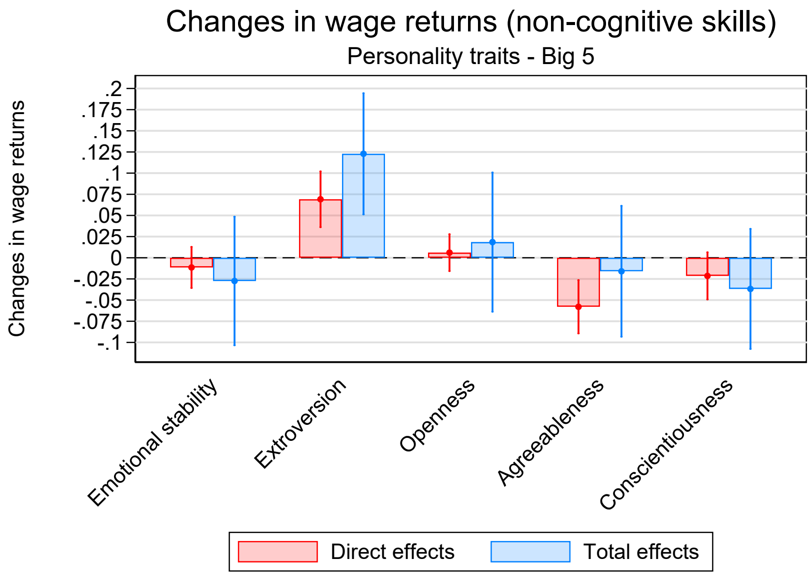
When considering the total effects, both verbal and math abilities have a sustained return to skills across cohorts M and Z respectively: 5.48% vs. 4.6% for verbal and 6.5% vs. 6.5% for math. Analyzing changes across cohorts, there is no evidence of significant variations in total returns on these skills. The returns remain 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%). This implies a growing significance of higher math proficiency within the labor market (3.46 percentage points increase). Similarly, GPA exhibits a substantial increase in returns, with an increment of nearly 9.6 percentage points. The majority of changes regarding the returns on cognitive skills occurred at the labor market level, with minimal differences observed within the educational setting.

[33]Figure 11, 12 and 13 all represent Δ_a^g for each a in our model, both cognitive and non-cognitive.

6.4.2 Changes in Returns to Non-Cognitive

Non-cognitive skills have a sizeable total return, relative to its direct return. This means that most of the increasing returns associated with non-cognitive skills go through the indirect effect of education. Figure 12 includes the change across cohorts in returns to a σ increase in each skill.

Figure 12: Changes in wage returns

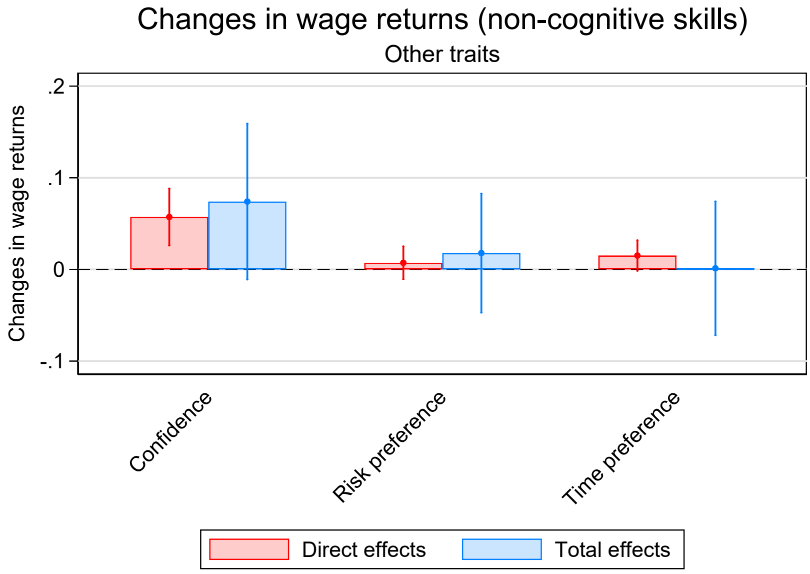


Notes: Change, Δ_a^g, in wage returns across cohorts expressed in percentage points (p.p.). The change is the difference between cohort Z and M in the wage return to a σ increase in each specific skill. Direct effects do not include the indirect effects of education. Total effects include the composite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

When considering total effects, the sizeable increase in non-cognitive skills returns is mostly associated with extroversion, among personality traits. For cohort M, a σ increase in extroversion resulted in a -0.3% direct return and a -4.57% total return, indicating a negative contribution from the indirect effect of education. On the other hand, for cohort Z, demonstrated a strong direct return of 6.53% and a total return of 7.7%, with a positive contribution from the indirect effect. This led to a substantial change of 6.9 percentage points for direct effects and 12.2 percentage points for total effects. Extroversion is one of the main component of the latent factor of social skills, confirming my results using the latent factors.

Figure 13 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. In cohort group M, individuals experienced a direct

Figure 13: 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.

return of 1.1% and a total return of 2.27%. In contrast, in cohort Z, the direct and total returns were 6.82% and 9.67% respectively. This substantial difference indicates a notable change in the returns on confidence, with an increase of 5.72 percentage points for direct returns and 7.40 percentage points for total returns. The findings suggest that individuals with higher levels of confidence not only have an increased return in the labor market but also benefit from an additional increase resulting from the indirect contribution of education. These results align with prior literature that highlights the importance of confidence as a strong predictor of tertiary education choices. Individuals with higher levels of confidence may be more likely to pursue further education and make choices that align with their career aspirations, leading to enhanced labor market outcomes.

7 Conclusions

The demand and supply of skills are undergoing significant transformations due to technological advancements, organizational restructuring, offshoring, and shifts in the labor force composition. On one side, the task content of the labour force has substantially changed, with a strong decline in routine tasks, mirrored by a large increase in social tasks (Autor et al., 2003; Deming, 2017). On the other side, from an empirical perspective on multidimensional skills, recent literature has highlighted the growing importance of social skills (Deming, 2017), a decreasing return to cognitive skills (Castex and Kogan Dechter, 2014; Edin et al., 2022) and an increasing return to education (Castex and Kogan Dechter, 2014; Ashworth et al., 2021). Overall, novel theoretical frameworks, including Acemoglu and Autor (2011), Demig (2017), and Deming (2023), have proposed novel models for understanding the intersection between technologies, tasks, and skills.

Relative to the previous literature, I employ an integrated framework developed, combining technologies, tasks, and multidimensional skills (Acemoglu and Autor, 2011; Deming, 2017; Deming, 2023). By incorporating this theoretical framework and drawing from previous empirical findings, I investigate changes in labor force tasks and their relationship to shifts in skill returns, as observed in recent decades. Unlike previous studies, I adopt a broader multidimensional perspective on human capital, recognizing that individuals possess cognitive, social, and non-cognitive skills, each of which contributes to their unique skill bundle (see also Deming, 2017). Non-cognitive skills, such as hard work, diligence, and conscientiousness, are distinct from social skills within this framework.

To empirically examine this theoretical framework, I utilize data from the German Socio-Economic Panel (GSOEP) and the European Skills, Competences, Qualifications, and Occupations (ESCO) database. By merging and linking these data, I can derive latent factors that capture the underlying characteristics of skills and tasks, thereby facilitating a more robust analysis within this framework. To the best of my knowledge, this is the first empirical paper to use these datasets combined, offering a more objective view of the German labour market. By analyzing data from Germany, I observe similar trends to those identified by Deming (2017) in the United States. Specifically, there is a rise in the social skills component of tasks performed by the German labor force, accompanied by a substantial decline in routine tasks. The demand for non-routine analytical (cognitive) tasks remains relatively stable. Additionally, there has been a notable increase in the employment demand for occupations emphasizing social skills, regardless of their cognitive task content. I employ a set of multidimensional skills that encompass cognitive, social, and non-cognitive dimensions. To analyze changes in the returns to these multidimensional skills, I utilize recent data from the GSOEP Youth questionnaire covering the early 2000s to 2020. I employ a dynamic model that incorporates joint schooling and labor market choices while considering the endogeneity of multidimensional skill measures to previous schooling choices and performances. Within this framework, I can distinguish between endogenous measures of skills and an exogenous measure of ability, leveraging a set of exclusion restrictions such as school recommendations and school reforms in Germany during the specified timeframe. Additionally, the dynamic model enables the estimation of direct and total effects, heterogeneous returns to skills, dynamic complementarity, and other essential treatment effects.

Consistent with the theoretical framework of Acemoglu and Autor (2011) and Deming (2017), my analysis reveals a significant 6.4 percentage point increase in the returns to social skills over the specified period. However, there has been no change in the returns to cognitive skills. Most notably, I document a negative shift of 3.1 percentage points in the returns to non-cognitive skills, controlling for cognitive and social skills as well as unobserved ability. This decline primarily stems from individuals with high non-cognitive skills having a comparative advantage in routine jobs. As predicted by Acemoglu and Autor (2011), the substantial decrease in the demand for routine tasks results in lower returns to skills. Moreover, high non-cognitive skills offset the increasing returns to social skills. There is no evidence of increasing returns to social skills for individuals with high non-cognitive skills, particularly among those with low cognitive skills, indicating that individuals employed in routine-intensive occupations and possessing low cognitive abilities are particularly affected by this shift. Overall, there is a substitution effect from high returns to non-cognitive skills to high returns to social skills. These findings are largely driven by changes in skill demand within the German economy, which are influenced by the comparative advantage and task intensity associated with each occupation. When the task content of routine jobs declines, individuals with a specific skill set, including high non-cognitive skills, who excel at performing these tasks, experience disadvantages, as predicted by Acemoglu and Autor (2011). This aligns with Deming's (2017) argument that individuals with high non-cognitive skills may derive greater utility from performing tasks that align with their skill set, and thus do not benefit from the increasing returns to social skills. Consistent with Deming (2017), I also find a significant shift in returns between social and cognitive skills among individuals in the upper tail of the skill distribution, highlighting a strong complementarity between these two skill dimensions. Finally, utilizing this model allows me to analyze the development of multidimensional skills. I find that grade retention in both primary and secondary education negatively impacts both cognitive and non-cognitive skills, but only grade retention in primary education impacts negatively social skill development. This suggests that social skills may develop differently: either earlier than other skills or that schooling may not be the primary environment to develop these skills.

Deming (2023), forthcoming for the *Handbook of the Economics of Education*, shows a strong interest in this line of research while using multidimensional human capital and investigating the changing structures and trends in the labour market. In the future, as already highlighted by Deming (2022) and Deming (2023), there are promising topics to be examined on multidimensional human capital, such as the development of multidimensional skills, the impact of educational expansion (with a strong effect on skill mismatch and overeducation), and the impact of novel technologies, such as artificial intelligence, which could start to replace abstract tasks.

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A Data

A.1 Data Cleaning and Descriptives

A.2 Measurement System for Tasks

Table 14: Measurement system for latent factors for task content

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

A.3 Measurement System for Skills

Table 15: Measurement system for latent factors θ^c, θ^{nc} and θ^{sc}

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

Figure 14: Distribution of skills across cohorts

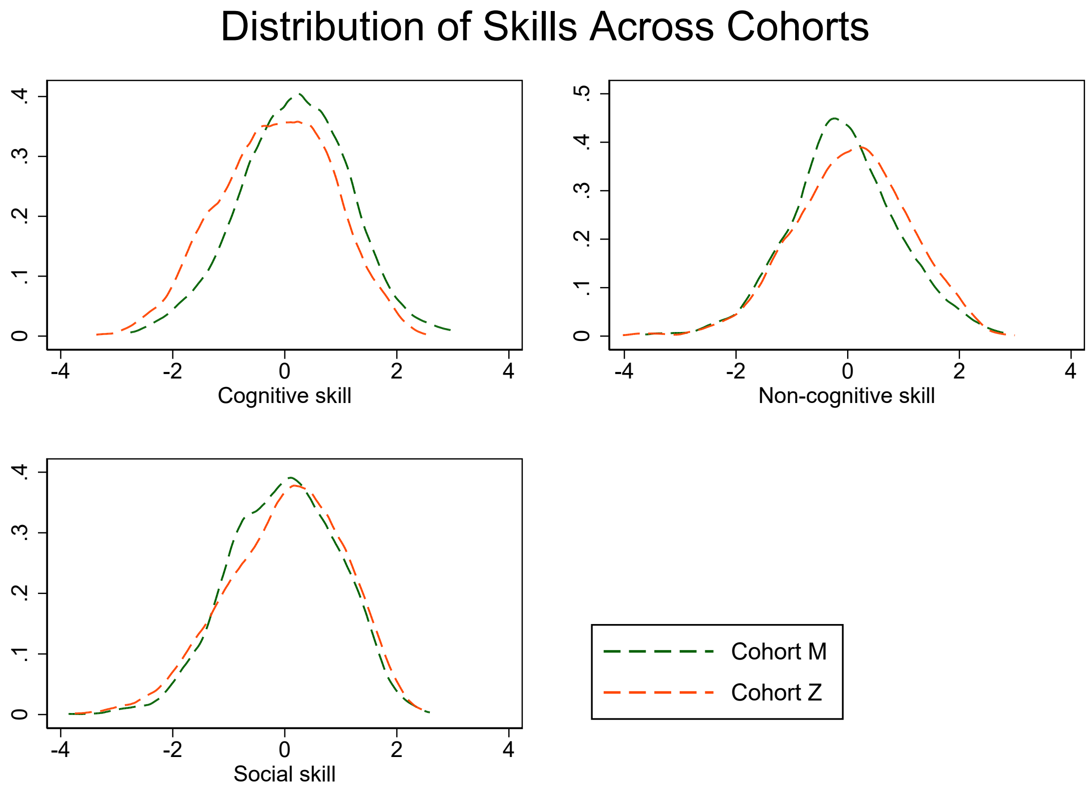


Table 16: Correlation across skill factors

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

Table 17: Model Selection

Cohort:	Number of heterogeneity types:	Seed (random starting values) 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

A.4 Wages

B Model

B.1 Model Selection

B.2 Counterfactual Simulation

To assess the treatment effects and establish confidence intervals, we employ a counterfactual simulation strategy (Cockx, Picchio, Baert, and 2019). In this approach, we conduct 999 simulations, randomly drawing parameters from the asymptotic normal distribution of the model's parameters. Subsequently, for each simulation draw, we utilize the probability types estimated through the EM algorithm to assign a heterogeneity type to each individual in the sample randomly. Based on these newly generated parameters, we simulate the complete sequence of schooling and labor market outcomes for each individual.

We also employ this counterfactual simulation strategy to evaluate the model's quality by generating a comprehensive set of outcomes and comparing them to the observed outcomes in the data. This evaluation is presented in Section B.3. 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.

Table 18: Goodness of Fit - Models Demographic Cohorts

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

B.3 Goodness of fit tables

B.4 Treatment Effects

I begin with representing log-hourly starting wages w as a function of individual characteristics, X, and observed skills, A:

$$w = f\Big(X, A\Big) \tag{20}$$

In this context, the wage return to skills can be calculated simply as $\frac{dw}{dA} = \frac{df(X,A)}{dA}$: 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, $S(X)$ and (ii) skills impact tertiary education, $E(X, S, A)$.[34] Therefore, this would be a stylized, yet more detailed equation of wages, relative to Equation 20:

$$w = f\Big(X, S(X), A(X, S), E(X, S, A)\Big) \tag{21}$$

[34] Schooling choices $S(X)$ are determined by individual observed characteristics. While skills, $A(X, S)$, are endogenously determined by both observed characteristics and schooling choices. Tertiary education, $E(X, S, A)$, is also influenced by individual observed characteristics, schooling choices, and skills.

Now, the returns to skills can be computed as:

$$\underbrace{\frac{dw}{dA}}_{\text{Total effect}} = \underbrace{\frac{\partial w}{\partial A}}_{\text{Direct effect}} + \underbrace{\frac{dE}{dA}\frac{\partial w}{\partial E}}_{\text{Indirect effect}} \tag{22}$$

where the total effect is decomposed into a direct and indirect component of the impact of skills on wages. Undoubtedly, skills significantly influence tertiary education, which in turn has a consequential effect on wages.

This framework provides a simple yet powerful approach applicable to diverse contexts in labor and education economics. It can be readily implemented using dynamic treatment effects models, enabling the estimation of treatment effects by considering counterfactual scenarios.

C Results

C.1 Changes in Complementarities

Table 19: Distribution of Changes Across Cohorts by Skill Bundle

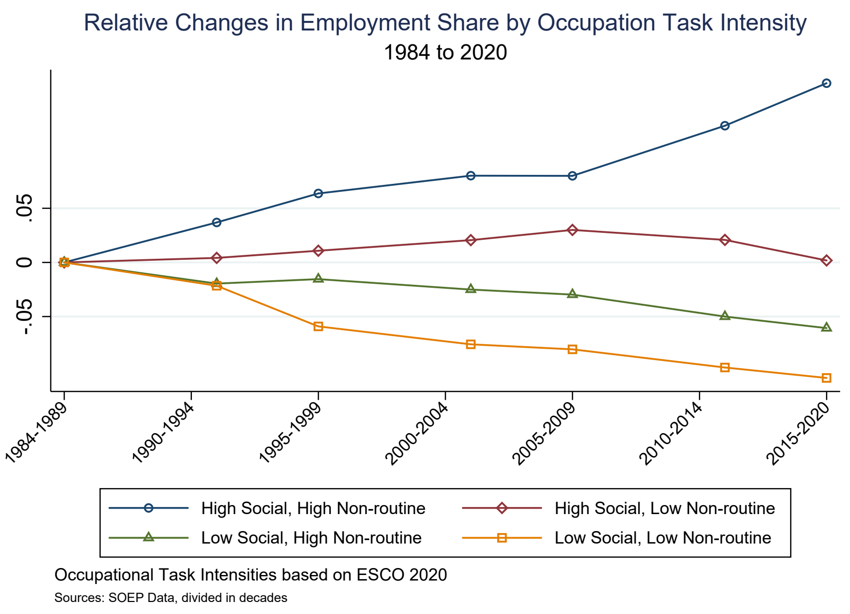
		$\theta^{sc}>0$				$\theta^{sc}<0$			
		M		Z		M		Z	
		Direct	Total	Direct	Total	Direct	Total	Direct	Total
$\theta^c>0$	Skills	0.065	0.006	0.202**	0.144*	0.168***	0.103*	0.207**	0.145
		(0.056)	(0.050)	(0.081)	(0.082)	(0.060)	(0.056)	(0.093)	(0.090)
	Cognitive skills θ^c	0.096***	0.033	0.053	0.015	0.122***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

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

Table 20: 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

Figure 15: Relative Changes in Employment Share by Occupation Task Intensity



D Robustness Checks

D.1 Task Content without Latent Factors

D.2 Changes in Present Value Earnings to Skills

D.3 Excluding Individuals by Year

D.4 Changes in Returns to Multidimensional Skills