Changes in Returns to Multidimensional Skills across Cohorts

Job Market Paper

Lorenzo Navarini*

Click here for the latest version

June 29, 2023

Abstract

This paper presents an empirical investigation based on an integrated framework including technological change, tasks, and skills, building upon the recent work of Acemoglu and Autor (2011), Deming (2017), and Deming (2023). I start by investigating the change in task content in Germany over the period 1984-2020, finding a strong decline in routine tasks, mirrored by a strong increase in social skills. By using a dynamic model of joint education and labour market choices, I estimate the changes in returns across a set of multidimensional skills. Along with the theoretical framework of Acemoglu and Autor (2011) and Deming (2017), I show evidence of increasing returns to social skills, consistent with the increasing demand for occupation intensive in social tasks. However, I also find decreasing returns to non-cognitive skills, a measure of diligence, and that high non-cognitive skills have offsetting effects on increasing returns to social skills. This happens because non-cognitive skills have a comparative advantage in performing routine tasks.

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), Deming (2017), and Deming (2023). The analysis begins by examining the changes in task content in Germany from 1984 to 2020, revealing a significant decline in routine tasks, accompanied by a substantial increase in social tasks. Utilizing a dynamic model of joint education and labor market choices, I estimate the changes in returns across a set of multidimensional skills. Consistent with the theoretical framework proposed by Acemoglu and Autor (2011) and Deming (2017), 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 I highlight the 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-based Approach, Dynamic Discrete Choice Model

*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 adopting novel technologies on the labor market? Which specific multidimensional skills (e.g. social and cognitive skills) are impacted by novel 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 (Acemoglu and Autor, 2011; Deming, 2017; Deming, 2023).

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) non-monotone changes in earnings and employment levels across the distribution of workers, i.e. polarization (see Acemoglu and Autor, 2011; Autor and Dorn, 2013), (ii) skill-biased technical change (SBTC), (iii) increasing returns to education and (iv) changes in the returns to multidimensional skills, favoring social skills (Deming, 2017; Deming, 2023).

Polarization has been observed in most advanced economies and has been attributed to the process of routinization, wherein occupations heavily reliant on routine tasks are being substituted by novel technologies such as computers and robots. 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). 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). Simultaneously, evidence suggests that computer and information technologies (IT) complement high-skilled workers by enhancing access to information (Autor et al., 2003; Beaudry et al., 2010; Michaels et al., 2014; Akerman et al., 2015).

[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).

In terms of skill-biased technical change (SBTC), the literature starts 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 been surpassed by an even greater demand for these skills. Building upon the pioneering work of Tinbergen (1974, 1975), the relative demand for skills is closely associated with technology, specifically the skill bias of technical change. 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.

However, this literature regards 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 a significant recent trend in the wage structure: rising returns to education and social skills, but declining returns to cognitive skills (Deming, 2023). Deming (2017) demonstrates that the labor market return to social skills was considerably higher in the 2000s compared to the mid-1980s and 1990s in the United States. Conversely, Castex et al. (2014) observe that a one standard deviation increase in the Armed Forces Qualifying Test (AFQT) score, a widely-used measure of cognitive skill, was associated with approximately 10 percent higher hourly wages in the 1980s and early 1990s, but only 4.5 percent in the 2000s and early 2010s. Outside the US, using test scores and administrative earnings records for about half of the Swedish male population, Edin et al. (2022) demonstrate a decline of approximately 25 percent in the return to cognitive skills between 2000 and 2013, paralleled with a strong increase in non-cognitive skills. Additionally, Beaudry et al. (2016) highlight a sharp decline in the demand for cognitive skill-intensive jobs around 2000.

These novel trends 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. This has been labeled as a task-based human capital approach.

In this paper, I present a novel 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 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. While social skills demonstrate an association with increasing returns, non-cognitive skills, when considered alongside cognitive and social skills, exhibit a declining return that effectively counterbalances the rising returns associated with social 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). By combining and linking these two datasets, I can extract a set of latent factors by significantly reducing the dimensionality of the measures of skill and task. This allows me to derive valuable insights regarding the underlying characteristics of skills and tasks, enabling a more robust analysis within the 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 requirements 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, 2016). 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 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 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 workers, indicating that low-cognitive employed in routine-intensive occupations are particularly affected by this change. Overall, I observe a substitution from high returns to non-cognitive skills to a high return to social skills.

This is largely accounted for by the changes in skill demand of the German economy, accounted by 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 development of multidimensional skills. I show that grade retention in both primary and secondary education, while impacting negatively both cognitive and non-cognitive skills, does impact differently social skills. This means that social skills may have a different development trajectory, rather than both cognitive and non-cognitive skills.

Overall, I offer a unified empirical framework for understanding technologies, tasks, and 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.

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, Murphy, and Pierce, 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 hypothesis (SBTC). A canonical model, pioneered by Tinbergen (1975, 1975), provides an explanatory framework for this phenomenon. It emphasizes that the return to skills (including college education) is influenced by a race between the growing supply of skills in the labor market and skill-biased technical change, wherein technological advancements are assumed to favor skilled workers (Goldin and Katz, 2008).

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. Technological change provides one possible explanation. The skills and tasks that cannot be substituted away by automation are generally complemented by it, and social interaction has—at least so far—proven difficult to automate (Autor 2015).

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, Green, and Sand, 2016; Castex and Dechter, 2014; Deming, 2017; and Edin et al., 2022); (ii) a change in the wage returns to education (Lundberg, 2013; Castex et al., 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.

A single index model of human capital would suggest that returns to college attainment and returns to cognitive skills follow the same pattern. Instead, the return to cognitive skills has declined since 2000. Castex and Kogan Dechter (2014) estimate labor market returns to both education and cognitive skill in the National Longitudinal Survey of Youth (NLSY) 1979 and 1997 samples, which allows them to compare estimates from the 1980s and 1990s to the post-2000 period. They find that a one standard deviation increase in the Armed Forces Qualifying Test (AFQT) score – a widely-used measure of cognitive skill – was associated with about 10 percent higher hourly wages in the 1980s and early 1990s but only 4.5 percent in the 2000s and early 2010s.8 In contrast, the economic return to a bachelor's degree increased by 6 percentage points unconditionally and by nearly 15 percentage points after controlling directly for cognitive skills in both waves (Castex and Kogan Dechter (2014)). Their results hold for all demographic groups and are robust to measurement error, test time and other details. Using test scores and administrative earnings records for roughly half of the Swedish male population, Edin et al. (2022) show that the return to cognitive skills declined by about 25 percent between 2000 to 2013. Beaudry et al. (2016) show that the demand for cognitive skill-intensive jobs began to decline sharply around 2000.

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), Adda et al. (2010), Baert et al. (2017), Heckman et al. (2018a, 2018b), Neyt et al. (2022), Ashworth et al. (2021).

2 Data

2.1 ESCO

ESCO (European Skills, Competences, Qualifications and Occupations) is the European multilingual classification of Skills, Competences and Occupations. ESCO works as a dictionary, describing, identifying, and classifying professional occupations and skills relevant for the EU labour market and education and training. Those concepts and the relationships between them can be understood by electronic systems, which allows different online platforms to use ESCO for services like matching jobseekers to jobs on the basis of their skills, suggesting trainings to people who want to reskill or upskill etc.

ESCO provides descriptions of 3008 occupations and 13.890 skills linked to these occupations, translated into 28 languages (all official EU languages plus Icelandic, Norwegian, Ukrainian, and Arabic). The aim of ESCO is to support job mobility across Europe and therefore a more integrated and efficient labour market, by offering a "common language" on occupations and skills that can be used by different stakeholders on employment and education and training topics.

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. In Appendix A.2, there is the complete set of skill groups I use for extracting a set of latent factors.

I categorize each occupation using the full set of around 13'000 skills in this 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 groups. In this way, for each occupation I have a set of binary outcomes, including complete information for each set of skill requirements.

2.2 GSOEP

I investigate the changes in educational and 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 et al., XXXX). 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[2].

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[3] (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[4]. Thus, I restrict our sample to those individuals for whom I have cognitive test data, resulting in a final sample of 4,055 individuals. After cleaning this sample, I end up with a total of XXXX individuals, for which I have both information on skills and educational pathways.

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 (and we may call them Millennials, following different definitions 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[5].

In terms of observed characteristics[6], I include a set of observables following the prior

[2]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.

[3] *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.*

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

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

[6]In the model section, I will refer to these characteristics as exogenous variables.

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	0.498	0.500	0.391	0.488
Mother High-Skilled	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, as in other papers (XXX), sex, migration background, born in Germany, siblings and birth year.

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[7].

I use other measures of non-cognitive skills, as included in the Youth questionnaire: such as the Big 5 personality traits, confidence, as well as risk and time preference (see Appendix X.X for further information).

In terms of skills, I include the following measures: Verbal, Mathematical and Abstract, GPA, Big 5 Personality traits, Confidence, Risk Preference and Time Preference. These are standard measures of cognitive and non-cognitive abilities, included in the literature on cognitive and non-cognitive abilities (see Humphries et al., 2020). In my paper, this large set of abilities is referred to multidimensional abilities: as in Todd and Zhang (2020), I do not use a simple factor constructed multiple measures of abilities, but I consider each single ability as having a specific effect on both educational and labour market outcomes.

[7]Especially, in terms of wage returns, this may actually be influenced by the poor local labour market of East Germany.

The participants took part in a validated short version of the well-established "I-S-T 2000 R" to measure cognitive skills (Amthauer et al., 2001), covering all three subsets which are verbal, numerical, and figural abilities (for details see Solga et al., 2005). I define two different abilities from this text: one measure constructed using verbal abilities and one measure constructed using both numerical and figural abilities (see more details in Appendix A). I also collect the GPA for each individual in German, Mathematics and the first language. In line with prior literature, I consider GPA as a measure of academic achievement and, therefore, as a cognitive ability (rather than a revealed non-cognitive ability).

The Big Five is measured using a validated 15-item questionnaire (Gerlitz and Schupp, 2005) that is commonly used in empirical personality research (see, e.g., Becker et al., 2012).

Within economics, some studies examine the impact of the "big-five" personality traits on various outcomes, including wages, employment, education, and marriage. However, many of the dynamic models in this literature that incorporate non-cognitive traits tend to represent these traits using a single factor, rather than utilizing multidimensional measures (Todd and Zhang, 2020). The Big 5 personality traits comprises the following dimensions: (1) extraversion: characterized by positive affect and sociability, and an orientation of one's interests and energy toward the outer world of people and things rather than the inner world of subjective experience; (2) neuroticism: characterized by a chronic level of emotional instability and proneness to psychological distress (i.e. with the opposite trait: emotional stability); (3) openness to experience/intellect: characterized by a tendency to be open to new aesthetic, cultural, or intellectual experiences; (4) conscientiousness: characterized by a tendency to be organized, responsible, and hardworking; and (5) agreeableness: characterized by a tendency to act in a cooperative and unselfish manner

This is one of the few paper examining the correlation of personality traits, educational choices and labour market outcomes (Todd and Zhang, 2020).

Lundberg (2013) found positive correlations between personality traits (such as conscientiousness, agreeableness, and openness to experience) and college entrance. Dahmann and Anger(2014), Kassenboehmer, Leung, and Schurer(2018) and Schurer (2017) argued that educational experiences in secondary school and at university shape students' personalities.

Confidence is constructed using a set of questions on future expectations. The idea is that a confident individual will be more confident in his future outcomes, conditional on his other abilities.

Risk preference is assessed through the question, 'How do you perceive yourself: are you generally a person who is fully willing to take risks or do you prefer to avoid taking risks?' Participants responded using an 11-point scale, where zero indicates an aversion to risk and ten indicates a willingness to take risks. This question has been studied in various papers and has shown high correlations with both incentivized experimental measures and revealed behavior (see, for instance, Dohmen et al., 2011). Higher (lower) values on this scale are indicative of higher (lower) levels of risk-taking behavior.

To measure time preference, the participants rated how strongly they agree with the two statements "I abstain from things today to be able to afford more tomorrow" and "I prefer to have fun today and don't think about tomorrow" (reversed) on a 7-point Likert scale. We construct our measure of time preference by summing the standardized responses. The resulting score is well correlated with incentivized experimental measures of time preference. Higher (lower) values of this measure are correlated with higer (lower) discounting values.

I include a table of descriptive statistics for exogenous variables in table 1:

While I observe most of the educational career of individuals and their entrance in the labour market. College vs vocational vs apprenticeship.

I only select the wage on the first job after the formal end of the educational path and construct a wage selection binary outcome for those individuals who are not observed with a wage (starting wage). I, then, compute the log-monthly wage for each individual.

2.3 German Education System

"At the end of primary school education, primary schools recommend to families a secondary school type for their children. This recommendation is primarily based on school grades and therefore on previous performance. In some federal states, these recommendations are binding, which means that pupils cannot readily make a transition to a higher secondary school type other than the one recommended. In other federal states, however, families are not bound by the recommendation and can therefore choose the secondary school type for the child more freely. Students visit a comprehensive primary school usually until grade 4. Afterward, they are channeled into three different educational tracks at the lower secondary level, which traditionally have been organized in different types of secondary schools (for details and changes over time, see the next section). Teachers' track recommendations, which reflect the students' prior school performance, and parental choice steer allocation to the different tracks. Constantly over federal states and birth cohorts, regular secondary schools are leading to either lower (Hauptschulabschluss), intermediate (Realschulabschluss) or to upper (Abitur) secondary school certificates."

Therefore, we divide both high school tracks and high school diplomas into three different tracks.

Moreover, we use the recommendation from primary schools as a starting point for our model.

More information are contained in Appendix A.1.

2.4 Labour market outcomes

The most important labour market outcome of our analysis is log-monthly wage. However, we extend the analysis to other job characteristics too: (i) the skill level of the job, (ii) if the individual is mismatched relative to the job and (iii) the type of contract. These are all measures of labour market outcomes performances.

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

The European Skills, Competences, Qualifications and Occupations (ESCO) includes a set of 13,485 concepts for describing and defining essential and optional skills for a set of 3008 occupations, coded using ISCO-08. All of these skills are grouped over a hierarchical system of 4 different levels.

In this paper, the main point here is to reduce the dimensionality of ESCO Skill content by occupation. The great number of skill description is certainly a huge amount of information, but it cannot be used suitably for analyzing each occupation. Therefore, I need to reduce the dimensionality. At first, I group them using the 3 digits ESCO labels, by including also transversal skills and competences. In total, I am left with more than 300 measures of skill content, as a binary variable, for which a 1 defines if the occupation has, at least, 1 of the skill of the relative group.

Some jobs may present a high measure of non-cognitive (diligence) tasks while having also a high degree of social task content, e.g. service jobs, as the waiter or flight attendant. Other jobs may display a different set of task content bundle.

The 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 measure the different skill requirements.

Using this reduced set of skills, I have different ways of extracting information and I assume the existence of 3 different latent factors, that I can estimate using a measurement system.

I link this data to the core SOEP dataset, excluding individuals in the youth questionnaire, to validate the findings of my model.

3.2 Measurement system for skills

Using the SOEP Dataset, I have access to a large set of measures of cognitive and non-cognitive abilities[8]. 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.

Therefore, I link the questionnaire on cognitive tests (COGDJ)[9] with 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

[8]Use this paper.

[9]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)

the schooling skill of each individual[10].

Indeed, both contain a large set of measurements 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 the non-cognitive measurements: in Toppetta (2022), these are externalizing and internalizing non-cognitive 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}).

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 [11] As in Humphries and Kosse (2016), I estimate non-cognitive skills from a large set of measurements available in the GSOEP dataset: participation to 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 13. In comparison to Humphries et al. (2021), 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

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

[11] Cunha, Heckman, and Schennach (2010), Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020), Attanasio, Meghir, and Nix (2020), and Agostinelli and Wiswall (2020) use a measurement system with continuous items and explore fewer dimensions of human capital. For example, they explore only one dimension of socio-emotional development - instead of considering two dimensions of socio-emotional skills (i.e., internalizing and externalizing).

traits. In my analysis employing a dynamic treatment effect approach, I incorporate the notion of ability through the utilization of finite mixtures and an exogenous number of unobserved types. These unobserved types are assumed to possess distinct developmental traits and employ a set of skills in different ways (refer to the Model section for more details)[12].

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 uncorrelated ability identified using the same measurement system.

The set of measurement is consistently large for each of these measure. I use a non-linear factor model to identify these factors using a comprehensive and large set of measures (see Appendix X.X for more information).

For identifying θ^c, I use a set of $m^c \in M^c$ dedicated measurements:

$$m^c_{ij} = a_j + \lambda_{ji}\theta^c_i + \varepsilon_{ij} \tag{1}$$

Specifically, m^{*c}_{ij} maps into m^c_{ij} via a threshold model:

$$m^c_{ij} \tag{2}$$

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

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

these factors.

I also measure a latent factor capturing the aspirations of the individuals at the age of 17, which I denote with θ^{as}.

I estimate this set of non-linear models using an EM algorithm approach, following Chen et al. (2021). See more details in the Appendix. I estimate the latent factor by integrating it out of the likelihood function, once estimated.

In Appendix A.3, Table 13[13] contains the full measurement system for the latent factors. It consists of 75 measures for the cognitive factor θ^{c}, and of 76 measures for extracting 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 measure of the following skills[14]:

[INCLUDE TABLE WITH CORRELATION OF VARIOUS MEASURES]

Furthermore, I estimate a factor θ^{as} of career aspirations for each individual, where I include a set of career aspirations and attitudes towards success. This is a factor indicating that an individual has a clear preference for certain types of jobs and careers, which are more social and interactive. See the full list of variables for factor θ^{as} included in this measurement system in Appendix **??**.

Considering the large set of questions and measurements[15], the estimation of these factors is computationally expansive, but using an EM Algorithm, I save up time and estimate a clear factor of choices.

Using this method, I utilize a large set of information and I minimize attenuation bias linked to measurement error[16].

In the first step, I identify each of these 3 models, while, in the second step, I include

[13] 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 is crucial for identifying these factors.

[14] 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.

[15] This is a likelihood of 67 equations for θ^{c},

[16] See XXXX for more information about it.

these latent skills into a dynamic model of human capital accumulation, considering them as endogenous to prior educational choices.

First, I am going to present some descriptive and graphs of the identified latent factors and, then, I am going to describe the benchmark model for treating endogenous skills.

3.3 Initial evidences

The factor θ^c is, by construction, correlated with high standardized scores and grades.

Table 2: 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

I interpret the two latent factors identified using non-cognitive measures as non-cognitive and social skills. Table 3 includes the correlation between the three latent factors and the 16 questions included in the personal characteristics items (Big 5 questionnaires). Work carefully is the normalizing variable for θ^{nc}, while communicative is the normalizing variable for θ^{sc}: this is why these factors present a high correlation with these questions. Moreover, θ^{nc} shows a stronger correlation with measures as carry out duties efficiently, considerate and friendly, hunger for knowledge and curious, while negatively correlated with abrasive towards others, lazy, nervous. On the other side, θ^{sc} is positively correlated with being outgoing/sociable

In Figure 2, I show the relationship between these three different multidimensional skills. The main point 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. Furthermore, I employ a dynamic model of joint educational choices and labor market outcomes to estimate these returns. The model

Table 3: Interpretation of measures (Big 5)

Big 5 questions:	θ^{c}	θ^{nc}	θ^{sc}
Personal characteristics: work carefully	-0.0028	0.7424	0.1924
Personal characteristics: communicative	-0.0306	0.2231	0.8138
Personal characteristics: abrasive towards others	-0.0429	**-0.3074**	**0.1393**
Personal characteristics: introduce new ideas	0.0044	0.2684	0.5629
Personal characteristics: often worry	-0.0366	**-0.0113**	**0.0436**
Personal characteristics: can forgive others	0.056	0.2738	0.2328
Personal characteristics: am lazy	0.0825	-0.526	-0.028
Personal characteristics: am outgoing/sociable	-0.0038	**0.1576**	**0.8429**
Personal characteristics: importance of esthetics	0.097	0.2003	0.2517
Personal characteristics: am nervous	-0.0205	-0.1281	-0.2429
Personal characteristics: carryout duties efficiently	0.0918	0.7589	0.2841
Personal characteristics: reserved	0.0183	**0.0609**	**-0.5979**
Personal characteristics: considerate, friendly	-0.026	0.5058	0.2531
Personal characteristics: lively imagination	0.0617	0.1095	0.3122
Personal characteristics: be relaxed, no stress	0.0459	0.321	0.2916
Personal characteristics: hunger for knowledge, curious	0.2046	0.4528	0.2784

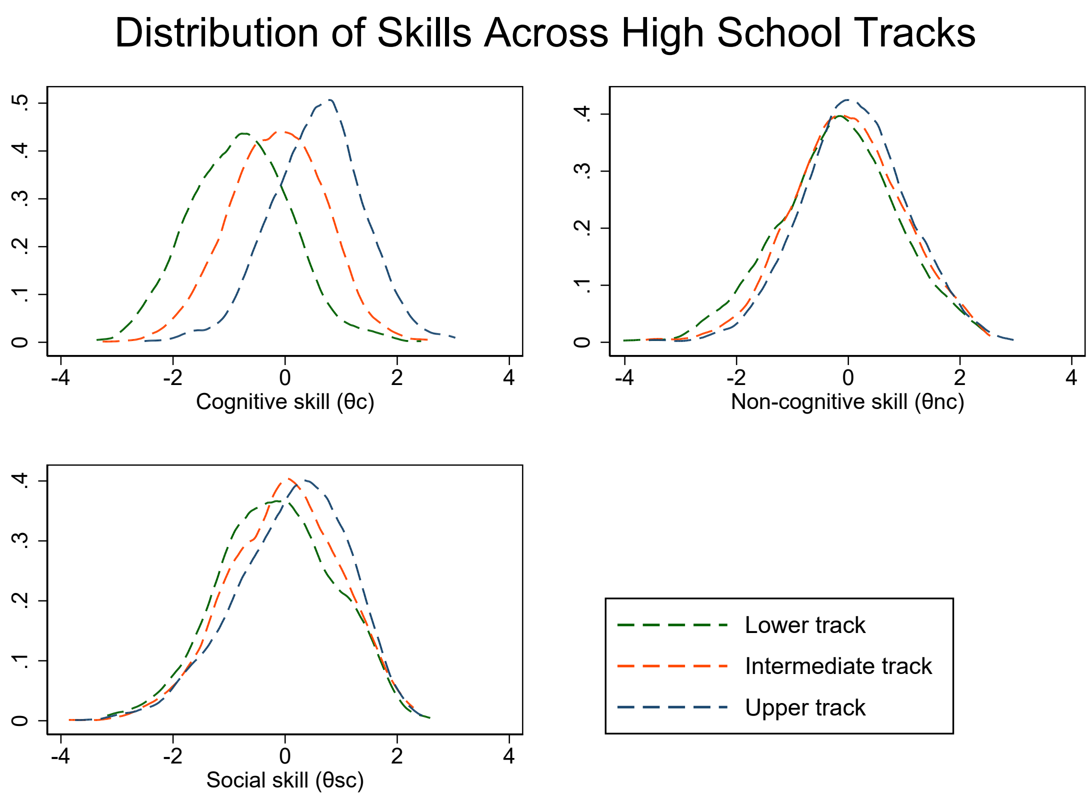


Figure 1: Distribution of skills across high-school tracks

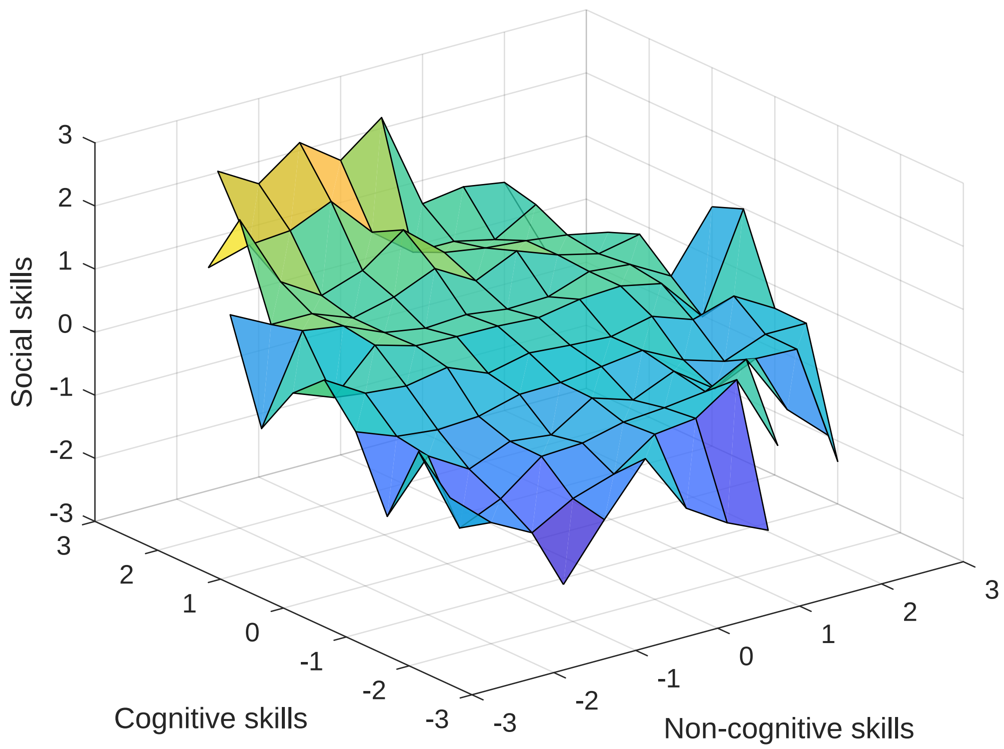


Figure 2: Relationship between skills

is a stylized version of a dynamic discrete choice model, as developed by the dynamic treatment effects literature (see Heckman et al., 2016, 2018a, 2018b, and Ashworth et al., 2021). This is used to control for dynamic selection and unobserved heterogeneity, by considering skills and educational choices as endogenous choices. 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.

In GSOEP, all individuals have completed primary education and are enrolled in secondary education at the age of 17. Therefore, I observe 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 multidimensional skill data for individuals measured 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:

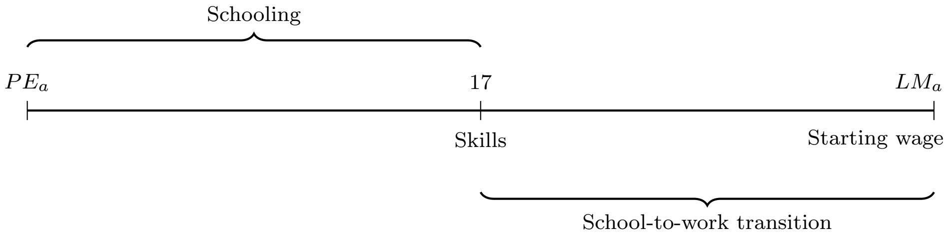


Figure 3: Stylized model

As explained in the first section, I represent each skill, $a_{i,d} \in A_{i,d}$, to be a function of schooling choices, $S_{i,d}$ and individual characteristics, $X_{i,d}$:

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

Once realized, skills impact both post-compulsory education choices (after the age of 16)[17] and labour market outcomes.

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

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

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

4.2 Schooling

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 shown in Figure 4.

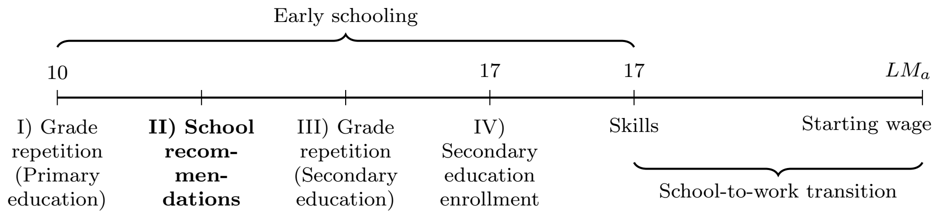


Figure 4: Model: schooling phase

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 have largely long-term adverse effects, with lower chances of graduating from high-school (Cockx et al., 2018).

At the end of primary education, also based on their observed grade repetition, individuals receive a school recommendation by 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 [18]. School recommendations are crucial in our model, because of the exclusion restriction we impose to identify unobserved heterogeneity: school recommendations influence school track enrollment, but it does 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 both greater skills[19]. In my model, unobserved heterogeneity captures this variation and it is interpreted as a source of ability differential among individuals[20]. It reflects differences in factors such as grit, motivation, pure ability,

[18] Some individuals may not receive a recommendation or I may not observe the recommendation of individuals in the dataset, see Appendix XX.X

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

[20] This is not the only source of identification of unobserved heterogeneity, as all outcomes are used to

and other aspects that influence both skill development and future outcomes.

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 recommendation. 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, 2021). In a counterfactual scenario, an individual who receives a higher recommendation 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 repetitions variables and school recommendation.

$S_{i,d}$ is a set which include $s_{i,d} \in S_{i,d}$ outcomes used as proxy for schooling: 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, $X_{i,d}$ [21]:

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

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.

4.3 Multidimensional Skills

In my setting, each skill $a_{i,d} \in A_{i,d}$ 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, $S^{-SR}_{i,d}$:

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

identify this ability differential: for instance, grade repetition and further exclusion restriction also aid the identification of unobserved heterogeneity.

[21] 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).

where each skill $a_{i,d} \in A_{i,d}$ is standardized to have mean 0 and standard deviation 1. Each skill a, 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

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 shown in Figure 5.

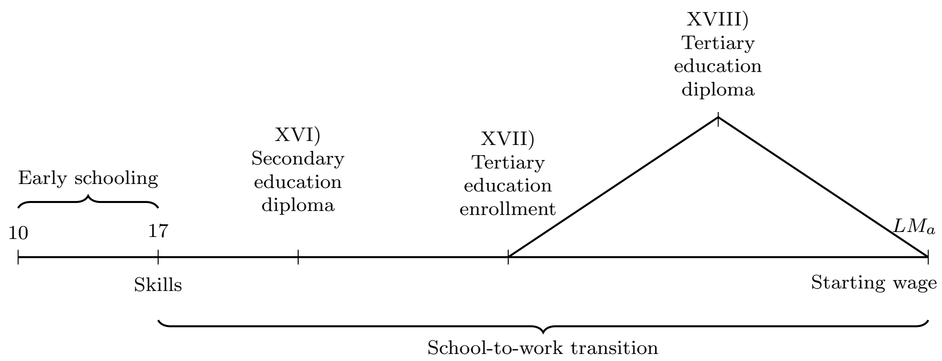


Figure 5: Model: school-to-work transition

Higher measures of both cognitive and non-cognitive skills are correlated with higher educational attainment and better outcomes. Once abilities $a_{i,d} \in A_{i,d}$ 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 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:

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

where $g(A_{i,d})$ includes a functional form for skills a 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:

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

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 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[22].

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 individuals, and in which $\omega^o_{k,d}$ 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, we deploy a finite mixture distribution to model the unobserved random variable $\eta_{k,d}$ (cf. Heckman and Singer, 1984; Arcidiacono, 2004)[23]. We assume that this distribution is characterised by an a priori unknown number of K different heterogeneity types with type-specific heterogeneity parameters $\omega^o_{k,d}$ for each outcome[24]. 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).

Firstly, the panel dimension of the data, specifically the autocorrelation of wages and choices given observed covariates, plays a vital role in identifying the returns associated

[22] 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.

[23] 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.

[24] See footnote 5.

with unobserved factors in both the outcome and choice equations. Secondly, as I will discuss further, the inclusion of exclusion restrictions in the form of variables that affect individual decisions but are not included in the potential wage equations is crucial for addressing the underlying selection issue.

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, 2021). 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 recommend a track. However, this does not produce an effect on future outcomes, except trough 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 recommendation to be excluded.

As the unemployment rate at the district 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 (cf. Heckman et al., 2018a, 2018b; Ashworth et al., 2021).

Second, we add the grade repetition in primary education as an explanatory variable for the subsequent educational outcomes but not for the labour market outcomes (cf. Baert, Neyt, Omey, and Verhaest, 2022). We thus presume the grade repetition in primary education to affect the labour market outcomes only indirectly through its effect on the grade repetition in secondary education. As the labour market effects of grade repetition in secondary education are unlikely to depend upon when it took place, this is a reasonable assumption.

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:

$$\mathcal{L}_{i,d} = S_{i,d} A_{i,d} E_{i,d} w_{i,d} \tag{11}$$

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

Therefore, it can be estimated in separate stages, with consistent results[25] However, when introducing unobserved heterogeneity, the likelihood specification becomes:

$$ln(\mathcal{L}_{i,d}) = \tag{13}$$

This is not additively separable anymore and it needs to be estimated all in once[26]

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 $k \in K$: $\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)$. Indeed, for each type k, we know the type-specific likelihood and the total expected likelihood weighted by the probability of being in each type k, $\pi_{k,i}$:

$$\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta) = \sum_{i=1}^{I} \ln \left(\sum_{k=1}^{K} \pi_{k,i} \prod_{o=1}^{O} \mathcal{L}_i^o(Z_i, R_i^o, V_i^o, \omega_k; \theta) \right) \tag{14}$$

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

$$\hat{p}_{k,i}(k|Z_i, R_i, V_i, \pi) = \frac{\pi_{k,i}\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)}{\sum_{k=1}^{K} \pi_{k,i}\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)} \tag{15}$$

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

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

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.

$$\sum_{i=1}^{I}\sum_{k=1}^{K}\hat{p}_{k,i}(k|Z_i, R_i, V_i, \pi)\left(\sum_{o=1}^{O}\ln(\mathcal{L}_i^o(Z_i, R_i^o, V_i^o, \omega_k; \theta))\right) \tag{16}$$

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 (See Appendix for opt).

This is our benchmark model, including a set of multidimensional skills.

5 Results

In this section, I document three main findings, related to the complex intersection between technologies, tasks, and skills (Acemoglu and Autor, 2011). In this 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, I further differentiate between *skills*, as endogenous endowments, and *abilities*, considered exogenous and innate, as explained in Section .

At first, I start by using the GSOEP Core data linked with the factors extracted by the ESCO skill requirements, as explained in Section X.X. 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 Deming (2017). Therefore, a substantial decline in routine tasks is 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 I introduced in Section B.4[27]. 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.

In the third subsection, I link the previous subsections, 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 increasing returns to social skills.

5.1 Changes in Tasks

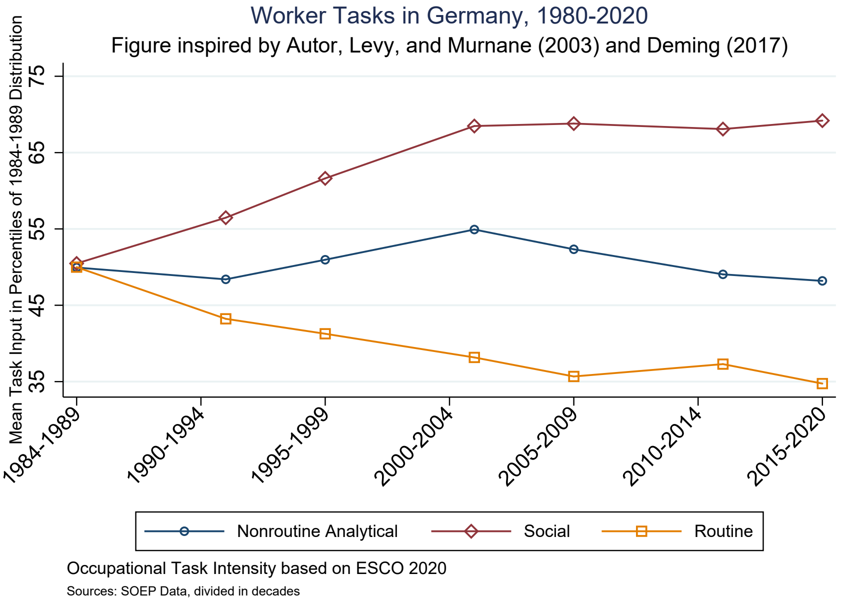
I will start by presenting the trends in task content of occupations and employment growth in Germany from 1984 to 2020. Figure 6 replicates both Figure I of Autor, Levy and Murname (2003) and Figure III of Deming (2017) using data from the German SOEP and the ESCO skill requirements, as presented in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

I follow the construction of Deming (2017): each task measure variable has a mean of 50 centiles in 1980 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 1980. Relative to Deming (2017), I estimate task measures using a factor extracted from a large set of descriptions of skill and task

[27]See Appendix B.2 for further information on the simulations for estimating counterfactuals and the relative standard errors

requirements by occupations in Europe, using data from ESCO, as explained in Section 2.1.

Figure 6: Worker Tasks in Germany, 1984-2020

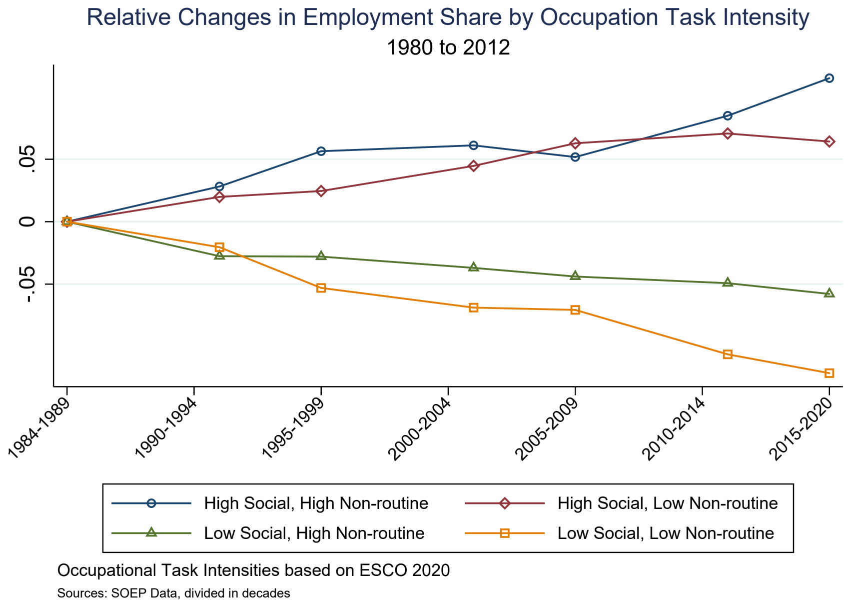


Notes: Figure 6 is constructed to parallel Figure I of Autor, Levy and Murnane (2003) and Figure III of Deming (2017), but for the German economy. Task measures are factors extracted by a large set of skill requirements and task descriptions by occupation (ESCO). Data are aggregated to industry-education-sex 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.

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 decline by a stark -30%, comparable to the results of Deming (2017). The decline in routine tasks essentially mirrors the growing importance of social skills 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 at a stable level relative to 1984. Overall, this is consistent with the sharp decline of nonroutine analytical (cognitive) task measures observed by Deming (2017) in the United States starting from the early 2000s.

As in Deming (2017), I control for possible skill upgrading as a result of the high correlation between social and nonroutine analytical skills task measures. 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: 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. See the text and Online Appendix for details on the construction of O*NET task measures and for examples of occupations in each of the four categories. Source: GSOEP Data.

By employing the theoretical framework put forth by Acemoglu and Autor (2011), it is possible to formulate several hypotheses regarding the returns on skills by examining the observed patterns of changes in 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.

Considering these three skill task measures, we can assume that the relative market price of social skill tasks has increased over time, mirroring a large decline in the relative market price of routine skill tasks. As these skill 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.

Therefore, I expect a large increase in the returns to social skills, as also predicted by 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 Heckman et al. (2006). Indeed, as Heckman et al. (2006) writes 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 (see the survey by Bowles, Gintis, and Osborne, 2001).

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. 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) [28] 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, $g = total$, 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.

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 tertiary education, with returns from this channel.

The returns to non-cognitive skills, θ^{nc}, conditional on both θ^c and θ^{sc}, are not sig-

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

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.

nificant. 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.

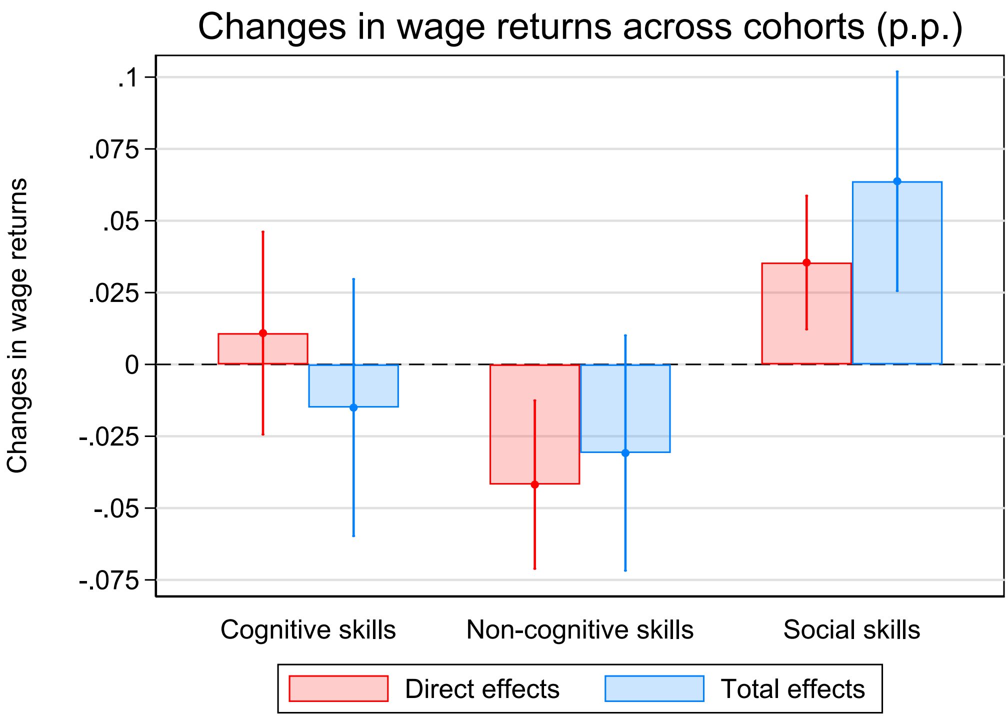
Using these returns, I can compare the changes across cohorts M and Z and simulate them using:

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

The results of this simulation are included in Figure 8. Overall, 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 component 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 between 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, therefore, it may be that there is further change captured by these effects. This is documented in the Section 5.2.1.

5.2.1 Changes in Complementarities

In this section, I compute further simulations to see how complementarities with multi-dimensional skills have changed over time.

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 Weinberger (2014) finds growing complementarity between cognitive and social skills across two cohorts of young men.

Table 5: Complementarities in returns to skills

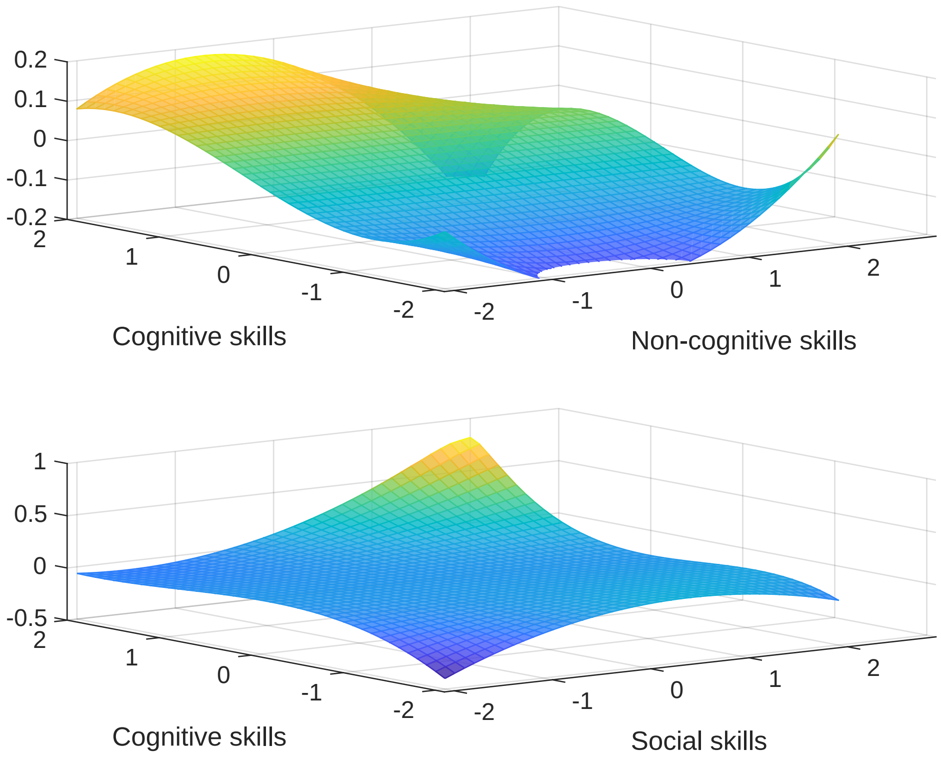
	(1) M		(2) Z		(3) Z-M	
	Direct	Total	Direct	Total	Direct	Total
Complementarities: cognitive and non-cognitive skills	-0.026	-0.031	0.030	0.033	0.056**	0.065***
	(0.024)	(0.020)	(0.031)	(0.029)	(0.025)	(0.010)
Complementarities: cognitive and social skills	-0.007	-0.006	-0.006	-0.005	0.001	0.002
	(0.027)	(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 $|theta^{sc}$, to the outcome of a combined σ increase in both skills. Using this approach, I can compute both direct and total effects.

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.

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 $j \in \{nc, sc\}$:

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.

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

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 simulation result is a matrix[29], which can be represented in a 3D graph, as in Figure 9.

This figure shows two interesting results.

First, as highlighted by the model in Deming (2017), there is a strong increase in

[29]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.

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. This is evident from Figure 9, where the largest changes in the returns to θ^{sc}, are concentrated among θ^{c} and θ^{sc} above the mean. This is the complementarity between cognitive and social skills highlighted by the model presented in Deming (2017).

Second, with increasing job task complexity, non-cognitive skills are especially important for those individuals with high cognitive skills, but lower non-cognitive skills (e.g. more creative individuals). 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. The more diligent an individual is, the more productive loss would come from performing too many skills. 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 task 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 result highlights the importance of 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.

For simplicity, I start by showing the returns to skills for high cognitive skills individuals. Essentially, I document a substitution effect from a high return to non-cognitive skill to a high return to social skill. Moreover, there is an offsetting effect of non-cognitive skills on increasing returns to social skills: social skills have a strong return for individuals with a non-cognitive skill below the mean.

Table 7 shows the changes in p.p. 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.

Table 6: Distribution of Changes Across Cohorts

	θ^c above mean, θ^{nc} below mean				θ^c above mean, θ^{nc} above mean			
	M		Z		M		Z	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Skills	0.017	0.076	0.142*	0.199**	0.102*	0.168***	0.149	0.211**
	(0.049)	(0.055)	(0.083)	(0.082)	(0.056)	(0.060)	(0.090)	(0.093)
Cognitive skills θ^c	0.039*	0.100***	0.012	0.051	0.065**	0.121***	0.093**	0.130***
	(0.021)	(0.032)	(0.039)	(0.045)	(0.027)	(0.031)	(0.036)	(0.048)
Non-cognitive skills θ^{nc}	-0.000	0.014	0.027	0.052	**0.053****	**0.070****	**-0.006**	**0.015**
	(0.021)	(0.034)	(0.036)	(0.043)	**(0.026)**	**(0.035)**	**(0.041)**	**(0.050)**
Social skills θ^{sc}	**0.016**	**-0.000**	**0.073****	**0.085****	0.023	0.009	0.033	0.044
	(0.022)	**(0.034)**	**(0.036)**	**(0.042)**	(0.026)	(0.034)	(0.035)	(0.047)

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.

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.

At last, individuals with high cognitive and high non-cognitive skills experience a negative change in returns to non-cognitive skills.

I further investigate this finding in Table 8. I compute the same returns for low 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	0.125***	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.

In this, I show that the negative change in returns to non-cognitive skills is even stronger for individuals with both low cognitive and non-cognitive skills. They experiece a negative change of 10.8 percentage points on returns to non-cognitive skills.

The findings on the offsetting effects of high non-cognitive skills is again true for individuals with low cognitive skills.

5.2.2 Mechanism

These findings 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.

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 in sorting into an occupation which is task intensive in either social, routine, or cognitive.

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)

Individuals with high non-cognitive skills have a large comparative advantage in performing routine tasks.

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 the 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).

As I showed in Section X.X, Germany, as most advanced economies, have undergone to a structural compositional change of the task content of its employment. As demonstrated in Deming (2017) and, previously, in Autor, Levy and M (2003), there has been a large decline in routine tasks, together with a large increase in social tasks. On the other side, the task content of cognitive (non-routine analytical) task remained stable.

Following Acemoglu and Autor (2011), we expect that this generates a change in relative market price for these tasks, generating a strong effect of skill groups with a comparative advantage over this set of skills.

Moreover, we document an increasing returns to social skills which can be explained in full using the theoretical framework of Deming (2017). Moreover, as Acemoglu and Autor (2011) can demonstrate, the increasing number of occupation with high social skills intensity does generate a strong return to individuals with higher social skills.

5.3 Development of Multidimensional Skills

In many cases, character skills acquired very early in life and strengthened throughout life are more important to a successful future than purely cognitive skills.

Competitive rewards in the labour market.

Furthermore, using this approach, I can also take a stance on skill development. Indeed, Deming (2017) is silent about the topic of skill development and it is clear, from more recent reviews, 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.

As in Deming (2022): "Higher-Order Skills Such as Problem-solving and Teamwork Are Increasingly Economically Valuable, and the Technology for Producing Them Is Not Well Understood."

A growing body of work emphasizes the importance of "non-cognitive" or "soft" skills like patience, self-control, conscientiousness, teamwork, and critical thinking. While such skills are clearly important, the very terms "soft" and "non-cognitive" reveal our lack of understanding about what these skills are and how to measure or develop them.

For example, Jackson et al. (2020) use survey evidence from ninth-grade students in Chicago public schools and find that schools with high "value-added" in promoting hard work and social well-being increase students' high school graduation and college attendance, even after accounting for their impact on academic achievement. Using data from the population of Swedish military enlistees, Lindqvist and Vestman (2011) estimate high labor market returns to both cognitive and non-cognitive skills, where the latter is measured using scores from a personal interview administered by a trained psychologist. Deming (2017) shows that the economic return to social skills in the United States more than doubled for a cohort of youth entering the labor market in the 2000s compared to the 1980s. In that study, discussed further below, I measure social skills by creating an index based on four factors: self-reported sociability; self-reported sociability at age six, as perceived by the adult respondent; number of clubs in which the respondent participated in high school; and participation in high school sports. Edin et al. (2022) find similar returns to social skills in Sweden, using administrative data from the compulsory military draft that required men aged 18 or 19 to be tested on cognitive and non-cognitive skills. Attanasio et al. (2020) find growing inequality in socio-emotional skills across two British cohorts born 30 years apart, using survey tools filled out by mothers (or in some cases teachers) about behaviors of their children. Each of these studies measures "non-cognitive" skills using whatever measures are at hand, rather than relating them conceptually to particular higher-order skills.

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

Table 10: Development of Multidimensional Skills

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

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 40% (23%) of an SD for primary (secondary) education for non-cognitive skills.

The evidence on social skills are different. Grade retention in primary education generates a loss in social skills in both cohorts of around 18% of a SD and 31% of a SD. 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 Changes in Present Value Earnings to Skills

I have just considered the value of starting wage in the main analysis.

In this setting, I can also consider the adjusted present value of earnings.

6.2 Changes in Starting Wage Returns to Skills

In the 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.

I begin with Table **??**, where I compute the wage return to a σ increase for cognitive and non-cognitive skills [30].

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. Conversely, in cohort Z, the majority of the return arises from direct effects. Consequently, the role played by the indirect effect of education in determining higher total returns for cognitive skills is comparatively smaller in cohort group Z.

Conversely, the indirect effect of education on non-cognitive skills has experienced a substantial increase. This contributes to the higher total effects observed for non-cognitive

[30] 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.

skills relative to cognitive skills, as highlighted by prior research (see XXXX).

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. This suggests that the majority of the change regarding the increasing returns on non-cognitive skills has occurred through the indirect effect of education. Individuals with higher levels of non-cognitive skills experience an increasing return on their education, which in turn generates a higher total return in the labor market. This result is closely connected to the literature on increasing returns to education and skills.

6.2.1 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.

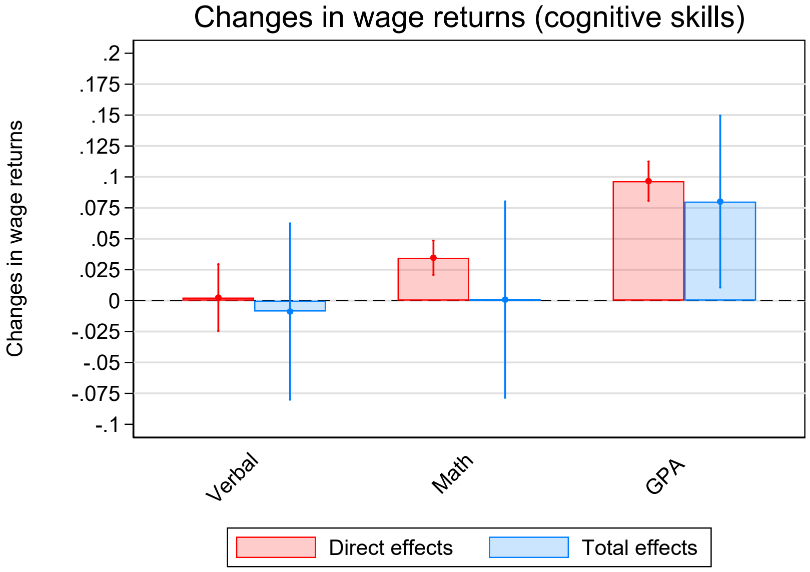
Figure 10[31] provides an overview of the changes in wage returns resulting from a σ increase in each cognitive skill across cohorts. The depicted changes encompass both the direct and total effects.

When considering the total effects, both verbal and math abilities have a sustained return to skills across cohorts M and Z of respectively: 5.48% vs. 4.6% for verbal and 6.5% vs. 6.5% for math (see Appendix X.X for the detailed results). 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. However, there is a notable increase in the total returns on GPA, mainly driven by its direct effects (8 percentage points): younger individuals with higher GPA exhibit better performance in the labor market.

Indeed, when analyzing the direct effects, there is no observable change in verbal

[31] Figure 10, 11 and 12 all represent Δ_a^g for each a in our model, both cognitive and non-cognitive. See Appendix X.X for detailed tables on returns.

Figure 10: Changes in wage returns



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

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.

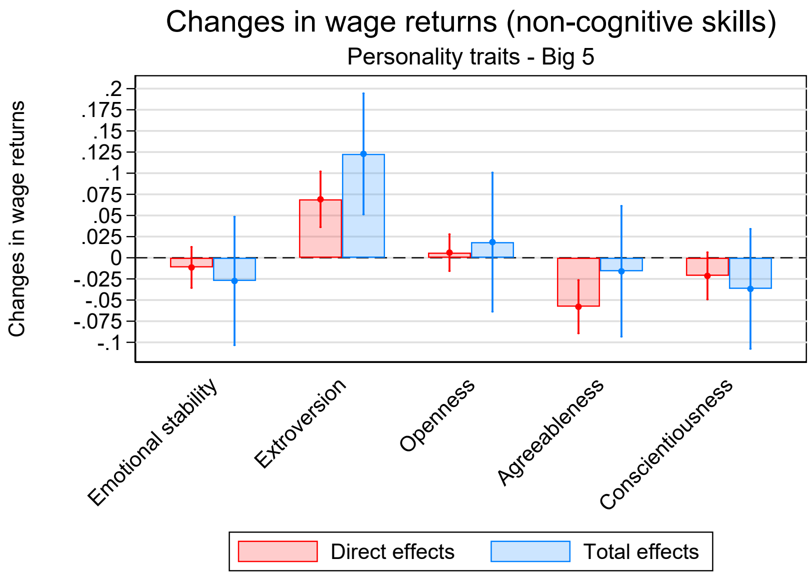
The majority of changes regarding the returns on cognitive skills occurred at the labor market level, with minimal differences observed within the educational setting. The increase in total returns on GPA can be seen as a response to the changing demands and expectations of employers, who increasingly rely on educational credentials as a signal of an individual's potential and suitability for employment. This interpretation aligns with the signaling theory, as it suggests that individuals with higher GPAs are effectively using their academic performance as a signal to distinguish themselves from others in the labor market. By achieving higher GPAs, these individuals are conveying their dedication, discipline, and intellectual abilities, which are desirable qualities sought by employers.

6.2.2 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 11 includes the change across cohorts in returns to a σ increase in each skill.

Figure 11: Changes in wage returns



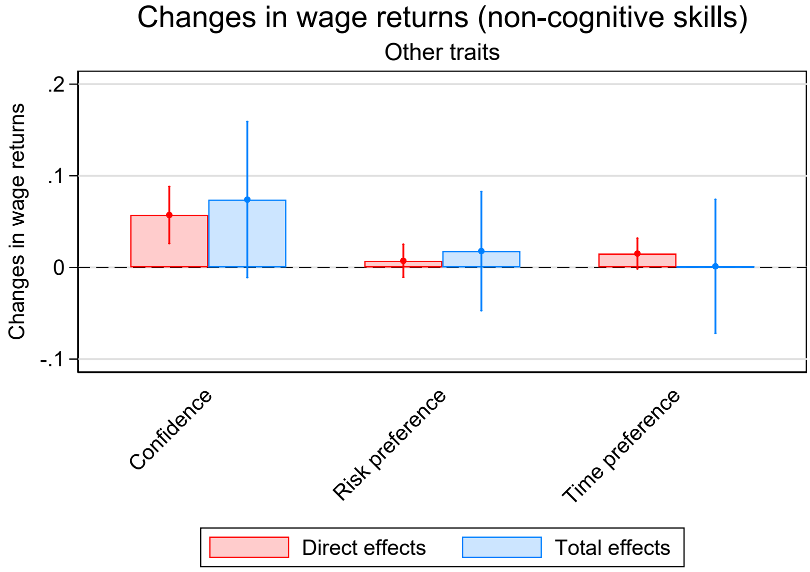
Notes: Change, Δ_a^g, in wage returns across cohorts expressed in percentage points (p.p.). The change is the difference between cohort Z and M in the wage return to a σ increase in each specific skill. Direct effects do not include the indirect effects of education. Total effects include the composite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

When considering 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. Conversely, 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. Higher levels of extroversion are not only associated with increased returns in the labor market but also within the educational setting.

Figure 12 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 return of 1.1% and a total return of 2.27%. Conversely, 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

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.

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 increasing 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.

6.3 Changes in Educational Returns to Skills

The previous findings indicate that greater returns on non-cognitive skills are linked to a larger indirect effect, which operates through educational attainment and educational returns. It is observed that non-cognitive skills now yield a higher educational return compared to previous periods, resulting in higher total returns to skills.

In this section, we compute the educational return to a σ increase in skill for the likelihood to obtain an upper secondary education degree, as well as enrolling and obtaining tertiary education.

Table 11: Changes in educational returns across cohorts

		(1) Upper secondary education	(2) Tertiary education enrollment	(3) Tertiary education diploma	(4) Starting wage
Cognitive skills	-	-0.040*	-0.014	-0.028	0.073**
		(0.021)	(0.036)	(0.025)	(0.036)
Non-cognitive skills	-	0.062***	0.112***	0.158***	0.146**
		(0.023)	(0.040)	(0.035)	(0.057)
	Extroversion	0.034*	0.087***	0.060**	0.123***
		(0.019)	(0.032)	(0.025)	(0.037)

Notes: Educational return to σ increase in the set of cognitive and non-cognitive skills for cohorts M and Z, with Z representing the younger cohort Generation Z. Changes in return is the difference between educational returns to a σ increase. Upper secondary education represents the percentage of individuals earning an *abitur* diploma at the end of secondary education. Tertiary education includes both university and advanced vocational experience.

Cognitive skills do not display any significant change in educational return to a σ increase in skills (except for a slightly significant negative change in obtaining an upper secondary education diploma).

Cognitive skills, for the most part, do not demonstrate any noteworthy change in the educational return resulting from a one standard deviation increase in skills. However, a slight but statistically significant negative change is observed in return for obtaining an upper secondary education diploma.

In contrast, as anticipated, non-cognitive skills exhibit increasing educational returns in various educational outcomes, including the likelihood of receiving upper secondary schooling, enrolling in tertiary education, and obtaining a tertiary education diploma. These positive effects on educational outcomes contribute to higher total returns in terms of starting wages.

7 Conclusions

In this paper, I estimated two models of human capital accumulation and labour market outcomes to estimate the change of returns to skills across two cohorts in Germany.

A Data

A.1 Data cleaning

A.2 Measurement system for tasks

Table 12: 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 13: 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

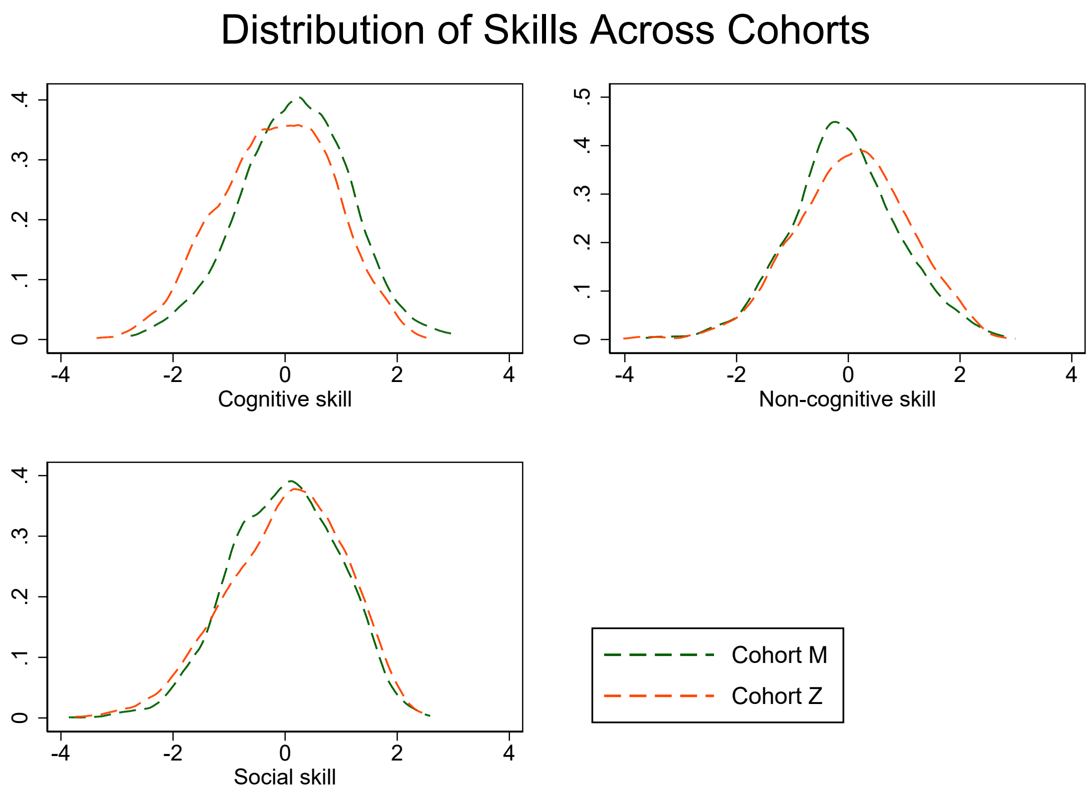


Figure 13: Distribution of skills across cohorts

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.

B.3 Goodness of fit tables

Table 14: 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.4 Treatment effects

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

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

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, $E(X, S, A)$[32]. Therefore, this would be a stylized, yet more detailed equation of wages, relative to Equation 20:

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

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

D Robustness checks

[32]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.