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Changes in Returns to Multidimensional Skills across Cohorts*

LORENZO NAVARINI[†]

Abstract

While social skills have become increasingly important in the labour market, other skills may have lost relevance. Estimating these changes is challenging because skills measured before tertiary education affect wages both directly and indirectly through educational sorting. This paper develops a sequential model with cognitive, social, and diligence skills measured at age 17 to estimate direct and total early-career returns across recent German cohorts, while accounting for unobserved ability. Direct returns to social skills increased by 6 percentage points, whereas total returns to diligence declined. Among individuals with low cognitive skills, returns to diligence fell by 10 percentage points, consistent with high-diligence workers sorting into routine-intensive occupations whose value declined under deroutinisation.

Keywords: Multidimensional skills; returns to skills; dynamic treatment effects.

JEL Codes: J24, I21, I26, O33.

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1 Introduction

Technical change and other forces are reshaping the labour market by changing the demand for different skills. As a result, returns to multidimensional skills have changed over time (Deming, 2023; Woessmann, 2024). A growing body of evidence documents a decline in returns to cognitive skills and an increase in returns to social skills, especially among high-cognitive individuals (Castex & Kogan-Dechter, 2014; Beaudry et al., 2016; Deming, 2017; Edin et al., 2022; Izadi & Tuhkuri, 2026).

However, existing studies typically use skills measured around the end of secondary education. This makes it difficult to separate the direct labour market value of skills from the role of later skill accumulation and educational sorting (Lochner et al., 2025). Higher education is central to this distinction because it is both an outcome of earlier skills and a channel through which those skills affect wages (Heckman et al., 2018a; Aucejo & James, 2021). The direct return to multidimensional skills captures their wage return holding later educational choices fixed, whereas the total return also includes the effect of skills on wages through those choices.

A further challenge is selection on unobserved ability, which is predetermined with respect to schooling choices. This latent heterogeneity may not only affect pre-tertiary skill measures (Deming, 2017) and wages (Lochner et al., 2025), but it may also shape sorting into higher education (Heckman et al., 2018a). This raises an important question: to what extent do changes in the returns to multidimensional skills reflect changes in direct returns, indirect returns through higher education, or selection driven by unobserved ability?

This paper estimates changes in returns to multidimensional skills across two recent German cohorts using data from the German Socio-Economic Panel (GSOEP), focusing on Millennials, born between 1987 and 1995, and Generation Z, born between 1996 and 2003. I construct latent factors of cognitive, social, and diligence skills at age 17 from more than 150 items, including standardised cognitive tests, school-performance measures, curricular and extracurricular activities, time and risk preferences, self-confidence, personality traits, and related indicators (Humphries & Kosse, 2017). The baseline factors are estimated on a pooled scale across cohorts. I also estimate returns under alternative measurement systems and report robustness checks using measurement-

invariant factors (Attanasio et al., 2020; Attanasio et al., 2025).¹ In contrast to studies that use a single non-cognitive factor, I separate social skills from diligence. I label the second non-cognitive factor diligence because it loads strongly on school effort, persistence, conscientious behaviour, and related measures. This distinction is important because diligence may be valued in different labour market environments than social skills, especially in routine-intensive or low-skilled occupations (Bowles & Gintis, 2002; Heckman et al., 2006).

I estimate returns to multidimensional skills using a sequential model of schooling choices, multidimensional skills, and starting wages (Heckman et al., 2018a; Humphries et al., 2023). The model starts from primary education outcomes, including teacher recommendations for secondary education tracks, and allows persistent latent types to affect each subsequent stage: secondary education choices, multidimensional skills, higher education choices, and wages. These latent types capture unobserved differences among individuals who are otherwise comparable in terms of observed characteristics, thereby helping to address dynamic selection in education and the labour market (Heckman et al., 2018a). The structure separates three objects that are usually confounded: skills measured at age 17, persistent unobserved heterogeneity formed before secondary schooling, and later educational choices through which skills affect wages.

Identification relies on the panel structure of the data and the sequence imposed by the model, together with exclusion restrictions (Hu & Shum, 2012; Heckman et al., 2016; Ashworth et al., 2021; Humphries et al., 2023). The setting provides institutional variation across German federal states and over time in whether teachers' track recommendations at the end of primary education are binding. This variation shifts the recommendation environment, while the recommendations themselves are informative about students' early ability and therefore help recover latent types and predict realised secondary-school track enrolment. The key maintained restriction is that, conditional on observed characteristics, latent type, and realised track enrolment, school recommendations affect later skills, higher education, and wages only through their effect on realised track enrolment. I discuss these assumptions in detail and provide supporting validity checks.

The paper makes two main contributions. Methodologically, it provides a framework to estimate direct and indirect returns to multidimensional skills while controlling for unobserved ability

¹Unlike studies based on the NLSY79 and NLSY97, where non-cognitive measures differ across cohorts (Deming, 2017; Ashworth et al., 2021), the GSOEP provides a more comparable measurement environment. I nevertheless test measurement invariance and report robustness checks using alternative skill factors.

(Heckman & Navarro, 2007; Heckman et al., 2016). This matters because common approaches in the literature use education as a control when estimating returns to skills (Deming, 2017; Edin et al., 2022). Since skills are measured before tertiary education, education is not fixed when the skill is determined: it is a post-skill outcome and therefore an indirect channel of returns. Controlling for education removes part of the total return to skills and creates a bad control problem if the object is the total effect (Angrist and Pischke, 2009). Even when the object is the direct return, a bias remains due to dynamic selection: individuals with different measured skill levels who complete the same higher education degree are likely to differ in unobserved ability (Angrist & Pischke, 2009).

Substantively, the paper shows which skill bundles are increasingly or decreasingly rewarded in the labour market, and through which channels. It complements previous studies, such as Deming (2017), Edin et al. (2022), and Izadi and Tuhkuri (2026), with three main findings. First, the direct return to a one standard deviation increase in social skills rises by 6.5 percentage points across cohorts in Germany, consistent with the growing labour market value of social skills (Deming, 2017). Second, the total return to diligence declines by about 5 percentage points, mainly because diligence becomes less strongly linked to sorting into higher education. Third, this decline is concentrated among individuals with low cognitive skills: for this group, both direct and total returns to diligence fall by about 10 percentage points. Thus, the average decline in the return to diligence masks a larger loss for a specific skill bundle: low cognitive skills combined with high diligence. The main results are robust to alternative factor constructions, measurement choices, and specifications of latent heterogeneity.

I then provide evidence consistent with a demand-side interpretation of the decline in returns to diligence. Following Autor et al. (2003) and Acemoglu and Autor (2011), I interpret skills as productive inputs whose value depends on the tasks workers perform. I use detailed occupation-level task descriptors from the European Skills, Competences, Qualifications and Occupations (ESCO) database to construct measures of routine, social, and non-routine analytical task intensity for German occupations between 1984 and 2020. Employment shifted strongly towards occupations intensive in social tasks, while routine-intensive occupations declined. High-diligence workers are more likely to sort into routine-intensive occupations. In the context of declining routine-task employment, this sorting pattern is consistent with the larger decline in returns to diligence among

low-cognitive, high-diligence workers.

Related literature This paper contributes first to the literature on technical change, wage inequality, and polarization. A large literature studies how skill-biased technical change affects the wage structure and the skill premium (Bound & Johnson, 1992; Juhn et al., 1993; Acemoglu & Autor, 2011). Related work documents employment polarization, with employment rising at the top and bottom of the skill distribution and declining in the middle, as well as associated shifts in wage polarization and inequality (Autor et al., 2003; Autor et al., 2006). Similar patterns have been documented in Europe (Goos & Manning, 2007; Dustmann et al., 2009; Goos et al., 2009). In much of this literature, skills are proxied by education groups. This paper instead studies workers' multidimensional skills directly and shows that the consequences of labour market change differ sharply across skill bundles. In particular, deroutinisation is associated with losses for low-cognitive, high-diligence workers whose skills predict sorting into routine-intensive occupations. This finding connects to Acemoglu and Restrepo (2022), who show that wage declines among workers exposed to routine tasks account for an important part of changes in the wage structure.

Second, the paper contributes to the literature on changes in returns to multidimensional skills (Almlund et al., 2011; Deming, 2023; Woessmann, 2024). A growing body of work shows that human capital has several dimensions and that non-cognitive skills, personality traits, and social skills matter for labour market outcomes (Heckman et al., 2006; Lindqvist & Vestman, 2011; Humphries & Kosse, 2017; Guvenen et al., 2020; Lise & Postel-Vinay, 2020; Todd & Zhang, 2020; Hermo et al., 2022; Humphries et al., 2023; Izadi & Tuhkuri, 2026). Moreover, different skills may have different impacts on educational choices and outcomes (Lundberg, 2013; Heckman et al., 2018a; Aucejo & James, 2021). Closely related papers document changes in returns to specific skills: cognitive skills have become less rewarded in some settings (Castex & Kogan-Dechter, 2014; Beaudry et al., 2016), while social skills have become more valuable (Deming, 2017; Edin et al., 2022). This paper differs in two ways. First, I distinguish social skills from diligence rather than combining all non-cognitive skills into a single factor. This distinction matters empirically: social skills become more rewarded, while diligence loses value, especially among low-cognitive individuals. Second, I estimate both direct and total returns, so that changes in wage returns can be separated from changes in sorting in higher education. Indeed, the decline in returns to diligence

is mainly driven by a weakening link between diligence and higher education sorting.

The closest papers in this literature are Deming (2017), Edin et al. (2022), and Izadi and Tuhkuri (2026). Deming (2017) shows that social skills became more valuable in the United States and emphasises complementarities between cognitive and social skills. Edin et al. (2022) studies changing returns to skills in Sweden, while Izadi and Tuhkuri (2026) construct comparable skill measures across cohorts. These papers estimate returns to pre-market skills, often controlling for education or college attendance. I build on this approach but estimate a different object. Because skills are measured before higher education is completed, education is a post-skill channel rather than only a control. I therefore decompose total returns into direct wage returns and indirect returns through higher education sorting.

This distinction also separates the paper from the literature on sequential models of education, skills, and labour market outcomes with dynamic selection and unobserved heterogeneity. The dynamic treatment effect literature emphasises that returns to education and skills depend on selection into later choices and on unobserved heterogeneity (Heckman & Navarro, 2007; Heckman et al., 2016, 2018a, 2018b; Humphries et al., 2023). A related literature introduces multidimensional skills into dynamic models (Güvenen et al., 2020; Lise & Postel-Vinay, 2020; Humphries et al., 2023), and Ashworth et al. (2021) estimates changes in returns across cohorts using cognitive and non-cognitive skills. Lochner et al. (2025) uses panel data to estimate unobserved skill returns over the life cycle. In contrast, I model unobserved ability as a persistent latent component that affects measured multidimensional skills, educational choices and wages. This differs from papers such as Ashworth et al. (2021) and Heckman et al. (2018a), because measured multidimensional skills at age 17 are separated from latent types and modelled as endogenous outcomes of earlier histories. By modelling both measured skills and latent ability, the paper addresses two related concerns: bias from dynamic selection and the possibility that measured skills partly proxy for unobserved ability.²

Finally, the paper contributes to the task-based literature by linking worker-level skill bundles to occupation-level task content. Task-based models emphasise that skills are rewarded through the tasks workers perform and that technical change can substitute routine tasks while complement-

²By modelling age-17 skills as outcomes of earlier schooling histories, the paper also relates to the skill-development literature (Cunha & Heckman, 2008; Cunha et al., 2010; Heckman & Raut, 2016; Agostinelli & Wiswall, 2025; Sorrenti et al., 2025; Agostinelli et al., 2026).

ing social or analytical tasks (Autor et al., 2003; Acemoglu & Autor, 2011; Deming, 2017; Edin et al., 2022). Focusing on Germany, Spitz-Oener (2006), Koomen and Backes-Gellner (2022), and Rohrbach-Schmidt and Tiemann (2013) provide task-content measures using German labour market data. I complement this work by constructing measures of routine, social, and non-routine analytical task intensity using ESCO, an occupation-level database with detailed task descriptors for European occupations. This differs from papers that use O*NET-based task measures or proxy worker skills by education groups. It also differs from work such as Taber and Roys (2019), where skills and tasks are not modelled as distinct objects. In this paper, skills are individual characteristics measured at age 17, while tasks are occupation-level requirements. Linking the two makes it possible to show that diligence predicts sorting into routine-intensive occupations, providing evidence consistent with a demand-side interpretation of the decline in returns to diligence.

The rest of the paper is organised as follows. Section 2 introduces the data and describes the institutional context. Section 3 presents preliminary returns to multidimensional skills and assesses potential bias. Section 4 describes the empirical framework. Section 5 includes the results of the model and Section 6 presents task-based evidence consistent with the proposed mechanism. Section 7 presents a series of robustness checks. Section 8 concludes the paper.

2 Institutional context and data

This section presents the institutional background and the data used in the analysis. Section 2.1 describes the German institutional setting, and Section 2.2 introduces the German Socio-Economic Panel (GSOEP). Additional information on the data is provided in Appendix A: Data.

2.1 Institutional context

In Germany, compulsory schooling generally begins at age 5 or 6 and continues until age 18. Primary school (*Grundschule*), which usually lasts four years,³ provides foundational instruction in mathematics, German, and science. After completing primary school, students transition to secondary education.⁴

³In Berlin and Brandenburg, primary school lasts six years.

⁴Students may repeat a grade in both primary and secondary school. Grade retention is relatively common in Germany: 20.3% of students experience repetition during their school career, compared with an OECD average of

Before enrolling in secondary education, students also receive a recommendation for one of the secondary school tracks based on their academic performance and teacher assessments. In some federal states, this recommendation is binding, so students cannot easily enrol in a track different from the one recommended. In other states, the recommendation is non-binding, and families are free to choose the type of secondary school. Over the past decades, German federal states have repeatedly reformed this system. Several states replaced binding recommendations with non-binding ones, others moved in the opposite direction, and some changed the system more than once (Grewenig, 2022).

Secondary education is traditionally organised into three main tracks: the lower track (*Hauptschulabschluss*), the intermediate track (*Realschulabschluss*), and the upper (academic) track, which typically lasts until grade 12 or 13 and leads to the university entrance qualification, the *Abitur*. The lower and intermediate tracks mainly prepare students for vocational training, whereas the upper track provides the main academic pathway to higher education. As a result, track placement may affect subsequent skill development by exposing students to different curricula and learning environments. Although many school models now combine the lower and intermediate tracks, the upper track is still offered primarily by the *Gymnasium*, the academically oriented secondary school.⁵

Students completing the lower or intermediate secondary track generally proceed to vocational education and training, most commonly in the form of an apprenticeship. Apprenticeship training is the typical pathway into many skilled occupations. Students completing the upper secondary track, in contrast, usually continue to tertiary education. In Germany, tertiary education is primarily offered by two types of institutions: universities, which are more academically oriented, and universities of applied sciences (*Fachhochschulen*), which emphasise more practice-oriented training.

12.4% (OECD, 2013).

⁵Transitions to a higher track remain possible but are relatively rare. In 2000, for example, only 1.5% of students moved to a higher track between grades 5 and 9 (Grewenig, 2022).

2.2 Data

German Socio-Economic Panel (GSOEP) The GSOEP is a longitudinal household survey that began in 1984 (Socio-Economic Panel (SOEP), 2022). Since 2000, a questionnaire (*JUGENDL*) has been administered to respondents at age 17 and includes detailed information on education and standardised measures of cognitive and non-cognitive skills. Data from *JUGENDL* cover 9,361 individuals and can be linked to the panel. Among these respondents, cognitive test scores are available for 4,055 individuals born between 1987 and 2003.⁶ A more detailed description of the data and the factor construction is provided in Appendix A.1: GSOEP.

Multidimensional skills I use factor models to recover three latent skill dimensions from the available measures at age 17: cognitive, social, and diligence skills, denoted by θ^j for $j \in \{cog, soc, dil\}$.⁷

For cognitive skills, θ^{cog} , the baseline factor combines standardized test scores and school-performance measures, including GPA, as listed in Table 1. I assess the sensitivity of this measure to two alternative measurement systems. First, I estimate the factor using only standardized test-score items, excluding school-performance measures. Second, following Izadi and Tuhkuri (2026), I first standardize each observed measure within survey year and then re-standardize it in the pooled sample before estimating the factor. Appendix Figure 7 shows that the resulting cognitive-skill measures are highly correlated with the baseline factor.

I measure non-cognitive skills with two latent dimensions: θ^{soc} and θ^{dil} . Let m_{iz}^{nc} denote non-cognitive item z for individual i . In the baseline measurement system, both factors are estimated jointly from the age-17 non-cognitive items listed in Table 1:

$$m_{iz}^{nc} = a_z + \lambda_z^s \theta_i^{soc} + \lambda_z^d \theta_i^{dil} + \varepsilon_{iz}. \quad (1)$$

The first factor captures social skills, with high loadings on communicative, outgoing, and interpersonal measures. The second factor captures diligence, with high loadings on working care-

⁶After imposing the item-availability restrictions required to construct the baseline cognitive factor, cognitive skill scores are available for 3,560 individuals. Non-cognitive skill measures are available for the broader Youth sample. Starting wages are observed for a smaller subset of individuals, and the model includes selection equations for cognitive-test availability and wage observation.

⁷Heckman et al. (2006) and Deming (2017) proxy non-cognitive skills using normalised averages of the Rotter Locus of Control and Rosenberg Self-Esteem scales. By contrast, I recover latent factors from a broader set of observed measures, including locus-of-control items and self-esteem-related proxies.

Table 1: Measurement system for multidimensional skills

Measures	θ^{cog}	θ^{dil}	θ^{soc}
Cognitive tests (COGDJ)			
20 Analogies questions	<i>bin.</i>	x	
20 Arithmetic operator questions	<i>bin.</i>	x	
20 Figures questions	<i>bin.</i>	x	
Youth Questionnaire (JUGENDL)			
GPA (German, Math, 1. Foreign language)	<i>cont.</i>	x	
Advanced Course (German, Math, 1. Foreign language)	<i>bin.</i>	x	
Support tutor	<i>bin.</i>	x	
Upper track preferred certificate	<i>bin.</i>	x	
Parents show interest in ... [7 questions]	<i>bin.</i>	x	
Involvement in school [11 questions]	<i>bin.</i>	x	x
How often ... [12 questions]	<i>cont.</i>	x	x
Satisfaction with [4 questions]	<i>cont.</i>	x	x
Probability in %: .. [12 questions]	<i>cont.</i>	x	x
Willingness to take risks	<i>cont.</i>	x	x
Trust people [3 questions]	<i>cont.</i>	x	x
Have fun today, not think about tomorrow	<i>cont.</i>	x	x
Personal characteristics: work carefully	<i>cont.</i>	x	
Personal characteristics: communicative	<i>cont.</i>		x
Personal characteristics: ... [14 questions]	<i>cont.</i>	x	x
Frequency of being ... [4 questions]	<i>cont.</i>	x	x
Political interests	<i>cont.</i>	x	x
Locus of control [10 questions]	<i>cont.</i>	x	x
Number of close friends	<i>cont.</i>	x	x

NOTE.— The second column indicates whether the measure is binary (*bin.*) or continuous (*cont.*). An *x* indicates that the measure enters the corresponding latent-factor measurement system. θ^{cog} denotes cognitive skills, θ^{dil} denotes diligence skills, and θ^{soc} denotes social skills. The cognitive factor is constructed from standardized test items and school-performance measures. The diligence and social factors are constructed from non-cognitive measures in the youth questionnaire, including personality items, emotional states, confidence, locus of control, risk and time preferences, school involvement, and social-interaction measures. Bold rows highlight the normalizing measures for diligence and social dimensions. All factors are oriented so that higher values correspond to higher skills and are standardized in the pooled sample. Appendix Section A: Data provides the full list of items, the factor-loading patterns, and robustness checks using dedicated social and diligence measurement systems.

fully, carrying out duties efficiently, absence of laziness, and related conscientiousness measures.⁸

I assess the robustness of these non-cognitive skills using two alternative measurement systems. First, I estimate the two factors using only dedicated non-cognitive measurement items described in Appendix A.1: GSOEP. Second, I replace the baseline latent factors with the closest Big Five counterparts: extraversion for social skills and conscientiousness for diligence. These alternative measures are highly correlated with the corresponding baseline factors. Appendix Table 17 reports descriptive statistics for each skill factor by cohort, while Table 1 summarizes the non-cognitive items used in the measurement system.

⁸Appendix A.1: GSOEP reports the exploratory and confirmatory factor analysis used to motivate the two-factor specification and guide the interpretation of the factors (see Appendix Table 19). Appendix Table 18 relates the latent factors to the Big Five personality items.

Changes across cohorts This paper studies changes across two demographic cohorts: cohort M , born 1987–1995, and cohort Z , born 1996–2003 (see Appendix Table 17).⁹ Comparing changes in skill returns across cohorts requires that the latent skill vector $\Theta_i = (\theta_i^{cog}, \theta_i^{soc}, \theta_i^{dil})$ be measured on a common scale (Attanasio et al., 2020; Attanasio et al., 2025). Appendix Tables 14, 15, and 16 report likelihood-based tests of measurement invariance.¹⁰

For the baseline cognitive measurement system, the likelihood-ratio test rejects exact loading invariance. However, the information criteria point in the opposite direction: both AIC and BIC favor the loading-invariant specification. To further assess cross-cohort comparability, I also construct an alternative cognitive factor using a restricted item set, for which the likelihood-ratio test does not reject loading invariance ($p = 0.518$). Appendix Figure 7 shows that this measurement-invariant cognitive factor is highly correlated with the baseline cognitive factor.

For the social and diligence factors, the evidence goes in the same direction. Likelihood-ratio tests reject exact loading invariance for both factors, as shown in Appendix Table 16. However, both AIC and BIC favour the loading-invariant specifications for the social and diligence factors. I therefore use these factors in the robustness checks. Therefore, the main cohort comparisons are interpreted conditional on the pooled normalisation of the latent factors and are checked against alternative skill constructions designed to improve cross-cohort comparability.

Exogenous variables, choices and outcomes Table 2 reports observed characteristics for individuals in the two demographic cohorts. I include parental background variables to proxy for differences in early schooling investments, such as parental upper-secondary education, university completion, and high-skilled occupation. I also include geographical characteristics, namely whether the individual lives in a big or medium-sized city, rather than a small city or rural area, and whether the individual lives in West Germany.

Appendix Table 12 reports the number of observed values, means, and standard deviations for

⁹See more details in Appendix: Demographic cohorts. Aggregating individuals into these two pre-defined cohorts allows me to estimate clearer changes over time, while the available data at the year-of-birth level are too sparse to support the main analysis.

¹⁰Relative to Attanasio et al. (2020) and Attanasio et al. (2025), I rely on likelihood-ratio tests and information criteria because the measurement system is nonlinear and combines continuous, ordered, and binary indicators. For comparing wage coefficients, the relevant restriction is metric invariance: factor loadings must be comparable across cohorts, so that a one-unit change in θ_i^k would have comparable measurement content. Threshold or intercept invariance is stronger and is mainly required for comparing latent skill means across cohorts, which is not the main object of the paper.

Table 2: Exogenous variables, by cohort

	(1)		(2)	
	M (1987-1995)		Z (1996-2003)	
	Mean	SD	Mean	SD
Sex	0.496	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	1.623	1.340	1.467	1.534
Birth Year	1989.106	4.086	1999.410	2.254
Father Upper Secondary Education	0.195	0.396	0.179	0.384
Mother Upper Secondary Education	0.176	0.381	0.177	0.382
Father University	0.155	0.362	0.141	0.348
Mother University	0.106	0.308	0.115	0.319
Father High-Skilled Occupation	0.498	0.500	0.391	0.488
Mother High-Skilled Occupation	0.353	0.478	0.333	0.471
Big or middle-sized city	0.399	0.490	0.336	0.472
West Germany	0.793	0.405	0.837	0.369
Observations	4,931		4,430	

NOTE.— M denotes Millennials, born between 1987 and 1995, and Z denotes Generation Z, born between 1996 and 2003. Father and Mother Upper Secondary Education indicate whether the respective parent completed upper secondary education or holds an *Abitur*. Father and Mother University indicate whether the respective parent completed a university degree. Father and Mother High-Skilled Occupation indicate whether the respective parent works in an occupation classified as high-skilled in the GSOEP. Big or middle-sized city refers to the individual's place of residence at age 17. The table is constructed using the full Youth questionnaire sample.

the endogenous variables included in the model, separately by cohort. The table shows differences across cohorts in both early work experience and educational choices. Work experience at age 17 declined substantially for Generation Z. Differences in later educational choices are likely to reflect, at least in part, the younger age of individuals in this cohort and the fact that some of them are only observed in more recent years.

The model addresses these differences by specifying separate equations for the observed choices and outcomes, including cognitive-test availability and wage observation.¹¹ These equations allow selection to depend on observed characteristics, previous educational histories, and latent types. Thus, non-random observation of skills and wages is accounted for under the maintained assumption that, conditional on these variables, remaining missingness is not driven by unobserved shocks to later outcomes.

Because Generation Z is observed over a shorter post-schooling window, I focus on starting

¹¹The missingness of cognitive-test information and starting wages is not random. Appendix Table 11 compares observed characteristics by cognitive-test availability, separately for Millennials (M, born 1987–1995) and Generation Z (Z, born 1996–2003). The table shows that test availability is correlated with some background characteristics.

wages in the benchmark specification. I also report robustness checks using the present value of observed wages and re-estimating the model on a trimmed Generation Z sample that excludes the youngest cohorts.

3 Returns to multidimensional skills

Descriptive evidence Let Y_i denote the log hourly starting wage of individual i , and let $\Theta_i = (\theta_i^{cog}, \theta_i^{soc}, \theta_i^{dil})$ denote the vector of cognitive, social and diligence skills measured at age a . Individuals $i \in I$ of cohort $c \in C$ are endowed with observed characteristics X_i and an unobserved endowment η_i . Wages are assumed to be determined by $Y_i = f_c(X_i, \eta_i, \Theta_i, U_i) + \varepsilon_i^y$, where, in its simplest version, $U_i \in \{0, 1\}$ denotes higher education completion and the wage function f is cohort-specific. Table 3 reports a naive reduced-form regression, with and without controlling for U_i and X_i , estimating changes in the returns to multidimensional skills using the following specification:

$$Y_i = \phi_0 + \delta_c + \Phi_{1c}\Theta_i + \Phi_{2c}X_i + \Phi_{3c}U_i + \varepsilon_i. \quad (2)$$

This specification estimates the wage returns to these skills while controlling for observed characteristics and educational choices, allowing for cohort-specific effects.

This reduced-form regression has two main issues. First, higher education is realised after skills are measured, so U_i is itself an outcome of skills. Table 3 shows that the returns to skills are lower when controlling for educational choices.¹² This difference illustrates a classic “bad control” problem (Angrist and Pischke, 2009), as post-measurement educational choices are not fixed when skills Θ^i are determined. In the literature, these estimates are often interpreted as direct returns on wages, holding fixed the effect on selection into higher education (Edin et al., 2022).

However, even when considering direct effects, there remains potential bias from dynamic selection: individuals with different skill levels within the same educational attainment likely differ in unmeasured abilities η_i (Heckman et al., 2018a). That is, both Θ_i and U_i are themselves outcomes of η_i . For instance, two observationally identical individuals with different levels of cognitive skills who complete the same university degree are likely to have different levels of η_i . Appendix B.1: Bias in direct and total returns formalises these sources of bias.

¹²This is referred to as the remaining return when controlling for selection into college in Edin et al. (2022).

Table 3: Preliminary estimates of changes in returns to multidimensional skills across cohorts

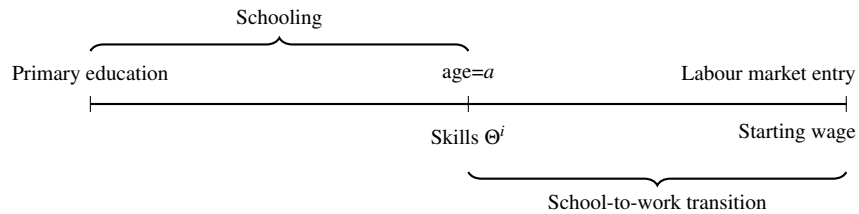
	Log hourly wage (first job)		
	(1)	(2)	(3)
Cognitive skills (θ^{cog})	0.163*** (0.019)	0.080*** (0.022)	0.030 (0.020)
Change across cohorts (θ^{cog})	-0.079* (0.031)	0.007 (0.036)	0.046 (0.034)
Diligence skills (θ^{dil})	0.044* (0.019)	0.041* (0.019)	0.016 (0.018)
Change across cohorts (θ^{dil})	-0.051 (0.032)	-0.051 (0.032)	-0.019 (0.028)
Social skills (θ^{soc})	0.044* (0.019)	0.014 (0.018)	0.001 (0.017)
Change across cohorts (θ^{soc})	0.009 (0.032)	0.043 (0.033)	0.034 (0.032)
Cohort-specific individual characteristics	No	Yes	Yes
Cohort-specific educational choices	No	No	Yes
R^2	0.050	0.093	0.242

NOTE.— Estimates of returns to multidimensional skills and changes across cohorts using a linear regression. Column (1) includes only Θ_i , column (2) includes X_i , and column (3) also includes educational choices. Individual characteristics include exogenous variables, as in Table 2. Educational choices include grade repetition in primary and secondary education, secondary education enrolment and diploma, tertiary education enrolment and diploma, as in Table 12. Starting hourly wages are log wages in the first observed job. The sample is restricted to individuals with observed wages. N is 2,219. Robust standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

4 A sequential model of education, skills and wages

In this section, I present an empirical framework to estimate changes in direct and total returns to multidimensional skills across cohorts, while accounting for persistent unobserved heterogeneity (Heckman et al., 2016; Humphries et al., 2023). Individuals make a sequence of educational choices, develop a multidimensional skill endowment, and enter the labour market with a starting wage, as stylised in Figure 1.

Figure 1: Timing of the model



The GSOEP provides data on multidimensional skills at age $a = 17$. In the German context, this timing is particularly important because students are sorted into different secondary school tracks after primary education. These pathways expose students to different curricula, peer groups, and

learning environments, implying that skills measured at age 17 should be interpreted as endogenous outcomes of earlier schooling (Cunha et al., 2010; Heckman et al., 2018a).

Section 4.1 introduces a simplified model and Section 4.2 discusses identification. Section 4.3 expands the simplified model including a broader set of choices.

4.1 Simplified model

Choices and outcomes At the end of primary education, individual i receives a school recommendation $R_i \in \{0, 1\}$, where $R_i = 1$ denotes a recommendation for an upper-secondary academic track. Let η_i denote persistent unobserved endowments affecting educational choices, skill formation, and labour market outcomes, observed by individuals, but unobserved by the econometrician.

These recommendations are based on information available before secondary schooling, including prior achievement and teacher assessments. They therefore provide an early signal of pre-secondary ability, when schooling is relatively homogenous before tracking. The recommendation is characterised by an index threshold-crossing rule:

$$R_i = \mathbf{1} \{ \phi_r(X_i, \eta_i, Z_i^p) - \varepsilon_i^r \geq 0 \}. \quad (3)$$

Let $Z_i^p = 1$ indicate that i lives in a federal state and belongs to a cohort exposed to a binding recommendation regime at the end of primary education (Grewenig, 2022). Based on this recommendation, students enrol in a secondary education track $A_i \in \{0, 1\}$, where $A_i = 1$ denotes enrolment in the upper-secondary academic track. Then:

$$A_i = \begin{cases} \mathbf{1} \{ \phi_s(X_i, \eta_i, R_i) - \varepsilon_i^s \geq 0 \}, & \text{if } Z_i^p = 0, \\ R_i, & \text{if } Z_i^p = 1. \end{cases} \quad (4)$$

Thus, when recommendations are non-binding, track enrolment is a choice, when recommendations are binding, individuals enrol in the recommended track.¹³

¹³Equation 4 is a stylised representation used for exposition in the simplified model. In practice, even binding regimes allowed deviations through entrance examinations or trial instruction, and Appendix Table 39 shows that the recommendation–enrolment relationship, while strong, is far from deterministic and is similar in binding and non-binding regimes. The full model does not impose this restriction: the binding-regime indicator Z^p enters the recommendation and secondary grade-repetition equations as an observed shifter, while track enrolment remains a

After secondary track enrolment, individuals realise endogenous skills:

$$\Theta_i = f_\theta(X_i, A_i, \eta_i) + \varepsilon_i^\theta, \quad (5)$$

where Θ_i is a vector of cognitive, social, and diligence skills.¹⁴

Then, individuals complete higher education in the school-to-work transition phase according to:

$$U_i = \begin{cases} \mathbf{1}\{\phi_e(X_i, \eta_i, A_i, \Theta_i) - \varepsilon_i^e \geq 0\}, & \text{if } A_i = 1, \\ 0, & \text{if } A_i = 0. \end{cases} \quad (6)$$

This restriction reflects the institutional setting: individuals who do not enrol in the upper-secondary academic track are not eligible to complete higher education.

Finally, starting log hourly wages are given by:

$$Y_i = f_y(X_i, \eta_i, A_i, \Theta_i, U_i) + \varepsilon_i^y. \quad (7)$$

This framework captures three central mechanisms. First, individuals sort dynamically into educational states based on both observed characteristics and latent endowments (Heckman et al., 2018a). Second, early educational choices affect later outcomes both directly and indirectly through skill formation and higher education completion. Third, observed wage differences by education and skills combine treatment effects with selection on observed covariates and unobservables, η_i .

This empirical specification can be interpreted as a sequential generalised Roy (1951) model, in which individuals sort across educational and labour market states according to observed characteristics and unobserved comparative advantage. At each decision node, individuals face state-specific expected outcomes, and their choices reveal how observed skills and latent heterogeneity

separate ordered choice depending on recommendations, observed characteristics, and latent type.

¹⁴Figure 8 in Appendix shows the sorting and skill development patterns for individuals with different skills into secondary education tracks. Regarding θ^{cog} , a clear pattern emerges. Those in the upper track exhibit higher cognitive skills. In contrast, the intermediate track aligns closely with the mean, while the lower track falls notably below the mean. These distributions may result from high-cognitive individuals sorting in the upper track. At the same time, it may also result from a focus on cognitive skill development in upper tracks relative to other tracks. Regarding θ^{dil} and θ^{soc} , the sorting pattern aligns with the one observed for θ^{cog} but is less strong. Overall, on average, individuals in the upper track show higher skills in all three multidimensional skills.

shape sorting over time. In this sense, the framework is closely related to the dynamic discrete choice literature (Humphries et al., 2023), but it does not require specifying a full utility function, solving a forward-looking optimisation problem, or modelling agents’ information sets explicitly (Heckman et al., 2018a; Walters, 2018). Instead, it approximates the implications of an underlying dynamic choice problem through a sequence of reduced-form choice, transition, and outcome equations. The model therefore lies between a reduced-form treatment effects framework and a fully structural dynamic model (Heckman et al., 2016): it preserves the sequential structure of educational choices and labour market outcomes, while remaining agnostic about the exact preferences and expectations that generate those choices.

4.2 Identification

Dynamic treatment effects assumptions I maintain two assumptions that are standard in the dynamic discrete choice and dynamic treatment effects literature (Heckman et al., 2018a; Humphries et al., 2023). First, all persistent unobserved heterogeneity affecting recommendations, track enrolment, multidimensional skills, higher education, and wages is summarised by η_i . Second, once X_i , η_i , and the current state are conditioned on, earlier history has no additional predictive content for the distribution of the next outcome. This restriction rules out unrestricted serial correlation in unobservables across stages (Heckman and Navarro, 2007). Conditional on η_i , later choices and outcomes are statistically independent of earlier shocks, so selection operates through the observed state variables and the latent factor (Heckman et al., 2018a).

The main limitation of this approach is that the analysis is *ex post*: the model can simulate the consequences of treatments that operate through observed states and choices, but it cannot recover counterfactuals that require a complete model of preferences, expectations, or policies that do not enter the observed state space (Stinebrickner and Stinebrickner, 2012; Wiswall and Zafar, 2015).

Unobserved heterogeneity I model η_i using a finite mixture distribution (cf. Heckman and Singer, 1984; Arcidiacono, 2004). Individuals belong to one of M latent types, $\eta_i \in \{1, \dots, M\}$, with type probabilities $\Pr(\eta_i = m) = \pi_m$. I assume the population type shares π_m are independent of observed characteristics X_i ($\eta_i \perp X_i$). With an appropriate number of mass points, mixture models of this form can accurately approximate arbitrary distributions of unobserved heterogeneity

(Heckman and Singer, 1984; Walters, 2018).¹⁵ Each type is associated with type-specific intercepts in the recommendation, track enrolment, skill production, higher education, and wage equations. Because η_i is latent and discrete, type labels have no intrinsic economic meaning. I normalise one type as the reference type in each outcome equation, so all type-specific intercepts are interpreted relative to this omitted type. Hence, types are not directly comparable across cohorts.

Treating the first-stage skill factors Θ_i as observed generated outcomes in the sequential model, and integrating over the latent finite-mixture type η_i , the joint contribution of the sequential model can be written as

$$\begin{aligned} & \Pr(R_i, A_i, \Theta_i, U_i, Y_i \mid X_i, Z_i^p) \\ &= \sum_{m=1}^M \pi_m \Pr(R_i \mid X_i, Z_i^p, \eta_i = m) \Pr(A_i \mid X_i, Z_i^p, R_i, \eta_i = m) \\ & \quad \times f_{\Theta}(\Theta_i \mid X_i, A_i, \eta_i = m) \Pr(U_i \mid X_i, A_i, \Theta_i, \eta_i = m) f_Y(Y_i \mid X_i, A_i, \Theta_i, U_i, \eta_i = m). \end{aligned}$$

The intuition is that, even among individuals with the same observed characteristics, some students may have a systematically higher propensity to receive academic recommendations, enter academic secondary tracks, develop skills, complete higher education, and earn higher wages. The model attributes this persistent component to η_i . This structure separates three objects that are usually confounded in reduced-form regressions. First, it separates selection into academic tracks from the effect of academic tracks. Second, it separates endogenous skills at age 17 from pre-secondary latent ability. Third, it separates the wage return to skills from selection into higher education and from persistent unobserved productivity.

The factor η captures variation already defined during primary education (ages 6-10), with the goal of tracing individuals as far back as possible to capture unobserved ability that already influences early treatments such as school track recommendations at this stage (Keane and Wolpin, 1997).¹⁶

¹⁵While η is discrete, it need not be interpreted as unidimensional; rather, it can represent a multidimensional ability, reflecting the idea that individuals in each discrete type may develop different combinations of skills and obtain heterogeneous returns.

¹⁶In the full model, the unobserved factor is already correlated with early educational choices at the age of 6. I recognise that relevant investments and choices may occur before age 6. The interpretation of η_i is therefore not purely genetic or innate, but rather as a summary of persistent early endowments observed by agents and institutions but not fully observed by the econometrician at the age of 6. Similar to the latent factor approach used for multidimensional skills, where a single factor is extracted from multiple measures, unobserved ability can be viewed as a latent factor

One could recover η_i in different ways, but this choice is not innocuous: there are several assumptions to be made about the nature of the unobserved factor. For instance, Heckman et al. (2018a) and Ashworth et al. (2021) estimate an unobserved factor that drives schooling choices and labour market outcomes and is interpreted using the ASVAB test scores. This approach does not distinguish between endogenous skills from exogenous ability. My approach builds on Humphries et al. (2023): observed skills Θ_i are measured in a first stage, and the unobserved factor is conditional on the prior schooling level attained by the age of the test. However, Humphries et al. (2023) restrict latent types to affect only educational decisions and outcomes. My approach departs from theirs by explicitly incorporating these latent types directly into the skill development function, which properly allows for endogenous correlation between the interpretable skills and the unobserved factor.¹⁷

School recommendation reforms Institutional variation in binding school recommendation regimes Z_i^p over time and across federal states shifts the recommendation environment (Grewenig, 2022). The maintained assumptions are

$$Z_i^p \perp \eta_i \mid X_i$$

and

$$Z_i^p \not\rightarrow (\Theta_i, U_i, Y_i) \quad \text{except through } (R_i, A_i).$$

The first assumption states that, conditional on observed characteristics, exposure to a binding recommendation regime is orthogonal to latent type. The second condition states that any effect of the regime on later skills, higher education, and wages operates through school recommendations and realised track enrolment.¹⁸

Appendix Tables 37 and 38 assess the empirical relevance of this institutional variation. Exposure to a binding recommendation regime changes the composition of school recommendations

that drives systematic differences in choices, skill formation, and outcomes among otherwise observationally similar individuals (Aakvik et al., 2005).

¹⁷Another approach, as in Joensen and Mattana (2021) and Bonhomme et al. (2022), is to estimate η_i using k -means clustering in a grouped fixed effects model.

¹⁸The simplified model abstracts from additional early schooling margins through which the binding-recommendation regime may operate. In the full model, I allow Z_i^p to enter not only the recommendation equation but also the secondary grade repetition. The exclusion restriction should therefore be interpreted as requiring that, conditional on observed characteristics and latent type, the reform affects later skills, higher education, and wages only through the modelled early schooling states.

across categories, while its effects on realised track enrolment are small and statistically insignificant.¹⁹ This pattern is consistent with high compliance with school recommendations under both regimes (Appendix Table 39). The reform should therefore not be interpreted as a stand-alone instrument for realised track enrolment. Its relevant first stage is instead the effect on the recommendation process itself: Z_i^p shifts the conditional distribution of recommendations R_i , while realised enrolment A_i remains strongly tied to recommendations in both institutional regimes.

Selection in high-school tracks Indeed, school recommendations play two distinct roles in the model. First, they are not assumed to be randomly assigned. They are allowed to be correlated with latent type,

$$R_i \not\perp \eta_i \mid X_i,$$

because they are observed early and summarise information about pre-secondary achievement, teacher assessments, and other persistent endowments. Among individuals with the same observed characteristics,

$$\Pr(\eta_i = m \mid X_i = x, R_i = 1) \neq \Pr(\eta_i = m \mid X_i = x, R_i = 0).$$

Thus, recommendations help recover the posterior type probabilities.

Second, recommendations predict realised track enrolment. The corresponding relevance condition is

$$\Pr(A_i = 1 \mid X_i = x, R_i = 1, \eta_i = m) \neq \Pr(A_i = 1 \mid X_i = x, R_i = 0, \eta_i = m).$$

Appendix Table 40 shows that school recommendations strongly predict realised secondary-track enrolment, supporting this relevance condition.

The exclusion restriction is that, conditional on observed characteristics X_i , latent type η_i , and realised track enrolment A_i , school recommendations do not directly enter later skill formation, higher education, or wage equations. Under this restriction, recommendations are type-informative early outcomes and predictors of track enrolment, but they do not directly affect later outcomes

¹⁹Appendix Table 36 reports the same checks in the simplified binary model. The recommendation strongly predicts academic-track enrolment, but the reduced-form effect of the binding reform on generic upper-track enrolment is similarly limited.

once track enrolment and latent type are held fixed.

This exclusion restriction would fail if recommendations affected later outcomes through channels other than track enrolment. Examples include direct effects on student motivation, parental investments, peer composition, or school resources, conditional on realised track and latent type. The interpretation therefore requires that these channels either operate through the modelled educational states or are absorbed by observed controls and latent type.

Appendix Figure 11 provides graphical evidence consistent with the identification structure of the model. School recommendations strongly predict later cognitive skills, which is consistent with recommendations being informative about persistent latent endowments η_i . At the same time, within a given recommendation category, individuals enrolled in different secondary school tracks display systematically different skill outcomes. Hence, there exists substantial unexplained variation among individuals who did not receive an academic recommendation but nevertheless enrolled in an academic track and exhibited strong skill development at age 17 (see Appendix Figure 11).

Identification therefore comes from the joint structure of the sequential model. The reform Z_i^p shifts the recommendation process; recommendations R_i help recover latent type and predict realised enrolment; and repeated later outcomes help identify the type-specific paths of skill formation, higher education, and wages.

Finally, it is important to note that school tracking policies have lasting effects on skill development at age 17, higher education choices, and wages, as highlighted in the higher education Equation 6 of the model. As shown in the simplified model, and in line with the institutional setting in Germany, individuals who do not enter an academic secondary track are not eligible to enrol in higher education. In this way, the model separates the contribution of early track assignment from that of later educational investments, allowing me to estimate how early educational sorting shapes the distribution of skills and early-career wage outcomes.

4.3 Full model

I expand the simplified model to account for a richer set of educational choices in both phases (Humphries et al., 2023). There are 5 choices in the schooling phase ($s \in \mathcal{S} = \{1, 2, 3, 4, 5\}$), a

cognitive-test availability node $q = 6$, three multidimensional skill dimensions $j \in \mathcal{J}_\theta = \{cog, dil, soc\}$, three choices in the school-to-work transition phase ($e \in \mathcal{E} = \{10, 11, 12\}$), and two labour-market outcomes ($w \in \mathcal{W} = \{13, 14\}$). Therefore, the subscript $t \in T = \{1, \dots, 14\}$ denotes the specific node of the model.

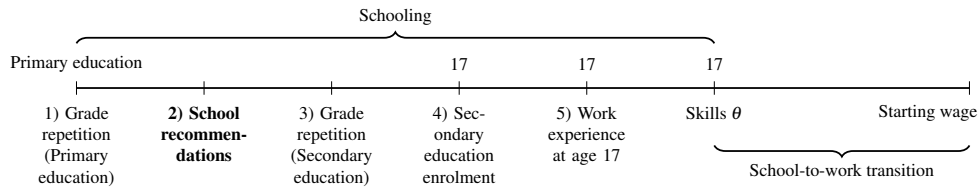
The core objects of the full model can be summarised as²⁰:

$$\begin{cases} D^s = \Psi^s \left(\phi_{l^s}^s(X, \eta, Z^s)_{l^s \in \mathcal{K}_s}, \varepsilon_{l^s}^s \right), \\ \theta^j = \tau^j(X, \eta, D^{\mathcal{S}}, Z^j) + \varepsilon^j, \\ D^e = \Psi^e \left(\phi_{l^e}^e(X, \eta, D^{\mathcal{S}}, \Theta, Z^e)_{l^e \in \mathcal{K}_e}, \varepsilon_{l^e}^e \right), \\ \log(\text{wage}) = f(X, \eta, D^{\mathcal{S}}, \Theta, D^{\mathcal{E}}, Z^w) + \varepsilon^w. \end{cases}$$

Here, D^s denotes the realised choice at schooling node s , $D^{\mathcal{S}} = (D^1, \dots, D^5)$ denotes the vector of realised schooling choices, θ^j denotes a multidimensional skill, D^e denotes the realised choice at school-to-work node e , and $D^{\mathcal{E}} = (D^{10}, D^{11}, D^{12})$ denotes the vector of realised school-to-work choices. The vectors Z^s , Z^j , Z^e , and Z^w collect variables specific to each choice or outcome stage, while the ε 's denote idiosyncratic shocks. The decision-rule functions Ψ accommodate binary, ordered, and multinomial choices. The index $l^t \in \mathcal{K}_t$ denotes the available alternatives at node t . Observed characteristics X are included in Table 2.

Schooling phase The schooling phase $s \in \mathcal{S}$ includes the following endogenous variables: grade retention in primary and secondary education, school recommendations, secondary education enrolment and work experience at age 17, as stylised in Figure 2.

Figure 2: Model (Schooling phase)



²⁰For ease of exposition, the displayed system suppresses the selection equations for cognitive-test availability and starting-wage observation. These nodes are included in the full likelihood as $q = 6$ and $w = 13$, respectively. Thus, cognitive skills contribute to the likelihood only when the relevant test information is observed, and starting wages contribute only when the first-job wage is observed.

At $t = 1$, students may repeat a grade in primary education, $D^1(\kappa_1)$, where $\kappa_1 \in \mathcal{K}_1 = \{0, 1\}$, with $\kappa_1 = 1$ defining repeating a grade. At the end of primary education, individuals receive a school recommendation ($D^2(\kappa_2)$). Let $\kappa_2 \in \mathcal{K}_2 = \{0, 1, 2, 3\}$ denote, respectively, no recommendation, lower, intermediate and upper secondary education recommendation.²¹ At $t = 3$, individuals may repeat a grade in secondary education before the age of 17 ($D^3(\kappa_3)$). Before skill measurement, individuals choose which track to enrol in secondary schooling, $D^4(\kappa_4)$ where $\kappa_4 \in \{0, 1, 2, 3\}$ follows the same categorical ordering as school recommendations. Finally, I account for work experience before age 17, $D^5(\kappa_5)$, where $\kappa_5 \in \mathcal{K}_5 = \{0, 1\}$.

The specification of the latent index $\phi^s(X, \eta, Z^s)$ includes time-invariant exogenous variables (X), s -specific observed outcomes (Z^s), including time-varying local labour market conditions (Unem^s), unobserved ability (η):

$$\begin{aligned} \phi^s(X, \eta, Z^s) = & \alpha_0^s \mathbf{1}_{\{s \in \{1, 3, 5\}\}} + \alpha^{s, X} X + \alpha^{s, \text{Unem}} \text{Unem}^s + \sum_{m=2}^M \mathbf{1}\{\eta_i = m\} \alpha^{s, m} + \alpha^{s, Z_i^p} Z_i^p \cdot \mathbf{1}_{\{s \in \{2, 3\}\}} \\ & + \alpha^{s, \text{delay}^{pe}} \text{delay}^{pe} \cdot \mathbf{1}_{\{s=2\}} + \alpha^{s, \text{delay}^{pe} \times X} \text{delay}^{pe} \cdot X \cdot \mathbf{1}_{\{s=2\}} \\ & + \alpha^{s, R_i} R_i \cdot \mathbf{1}_{\{s \in \{3, 4\}\}} + \alpha^{s, R_i \times X} R_i \cdot X \cdot \mathbf{1}_{\{s \in \{3, 4\}\}} \\ & + \alpha^{s, \text{delay}^{se}} \text{delay}^{se} \cdot \mathbf{1}_{\{s \in \{4, 5\}\}} + \alpha^{s, \text{delay}^{se} \times X} \text{delay}^{se} \cdot X \cdot \mathbf{1}_{\{s=4\}} \\ & + \alpha^{s, \text{hs_track_e}^{hs}} \text{hs_track_e}^{hs} \cdot \mathbf{1}_{\{s=5\}} \text{ for } s \in \mathcal{S} = \{1, 2, 3, 4, 5\}, \end{aligned}$$

which includes, depending on the node $s \in \mathcal{S}$, exogenous variation across states and year from the binding school recommendations reform in Germany from Grewenig (2022) (Z_i^p), grade retention in primary and secondary education (delay^{pe} and delay^{se}), school recommendations at the end of primary education (R_i), and secondary education track enrolment at age 17 (hs_track_e^{hs}). Moreover, this specification includes a set of interactions between observed characteristics and other endogenous variables to account for heterogeneity in the selection-into-treatment equation. For $s = \{1, 3, 5\}$, the decision rule function Ψ^s is binary, while for $s = \{2, 4\}$, it is ordered, given the hierarchical structure of high school tracks in the German system, as in other European countries (De Groote, 2025).

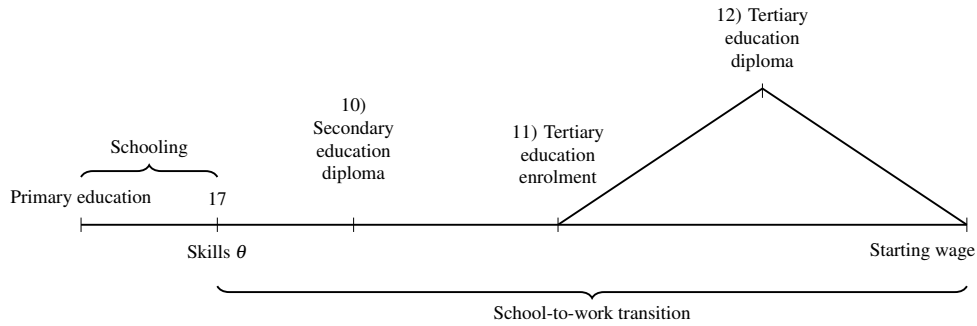
²¹The ordered specification uses the institutional hierarchy of German secondary tracks, which differ in academic orientation, curriculum, and eligibility for higher education. The restriction is that track choice can be represented by a single latent index with ordered thresholds.

Multidimensional skills At age 17, I model a set of multidimensional endogenous skills θ^j .²² In the benchmark specification, I first estimate the latent skill factors and then include the resulting factor scores in the sequential economic model.

Skills θ^j are assumed to be a linear function (see Appendix B: Model for the specification), which includes grade retention in primary and secondary education (delay^{pe} and delay^{se}) and secondary education track enrolment at age 17 (hs_track_e^{hs}), with a set of interactions to allow for heterogeneous skill effects of educational choices and treatments.

School-to-work phase Multidimensional skills θ^j enter the equations for obtaining a secondary education diploma in different tracks (or the relative probability of dropping out), enrolment and completion of a tertiary education degree:

Figure 3: Model (School-to-work transition phase)



Individuals realise a secondary education diploma, $D^{10}(\kappa_{10})$, with $\kappa_{10} \in \mathcal{K}_{10} = \{0, 1, 2, 3\}$ denoting dropout, lower secondary, intermediate secondary, and upper secondary education, respectively. If students obtain a degree above lower secondary education ($D^{10}(\kappa_{10}) > 1$), they can enrol in tertiary education ($D^{11}(\kappa_{11})$). After enrolling ($D^{11}(\kappa_{11}) = 1$), they can obtain a tertiary education diploma ($D^{12}(\kappa_{12})$).

The specification of the latent index $\phi^e(X, \eta, D^{\mathcal{S}}, \Theta, D^{\mathcal{E}}, Z^e)$ is given by the latent-index specification in Appendix B: Model. For $e = \{10\}$, the decision rule function Ψ^e is an ordered choice, while the decision rule is binary for $e = \{11, 12\}$.

²²Because cognitive test scores are observed only for a subset of respondents, the full model includes a selection equation for cognitive-test availability. This equation conditions on observed background characteristics, educational histories, and latent types. The maintained assumption is selection on observables and latent type: conditional on these variables, test availability is independent of the measurement error in cognitive skills and of later wage shocks.

Labour market outcomes Finally, after the school-to-work transition, individuals may have an observed first-job wage. Let $D^{13}(\kappa_{13})$ denote the indicator for observing a first-job wage. Conditional on $D^{13}(\kappa_{13}) = 1$, the starting log hourly wage at node $t = 14$ is assumed to be a linear function:

$$\begin{aligned}
f(X, \eta, D^s, \theta^j, D^e, Z^w) = & \alpha_0^w + \alpha^{w,X} X + \alpha^{w,Unem} Unem^w + \alpha^{w,delay^{se}} delay^{se} + \alpha^{w,hs} hs_track^{hs} \\
& + \sum_{j \in \mathcal{J}_\theta} \alpha^{w,\theta^j} \theta^j + \theta^{cog} (\alpha^{w,\theta^{cog} \times \theta^{soc}} \theta^{soc} + \alpha^{w,\theta^{cog} \times \theta^{dil}} \theta^{dil}) \\
& + \alpha^{w,TE} TE + \alpha^{w,TD} TD + \sum_{j \in \mathcal{J}_\theta} \alpha^{w,\theta^j \times TE} \theta^j \cdot TE + \alpha^{w,hs \times TD} hs_track^{hs} \cdot TD \\
& + \sum_{j \in \mathcal{J}_\theta} \alpha^{w,\theta^j, TD \times hs} \theta^j \cdot TD \cdot hs_track^{hs} + \alpha^{w,WE} Work_Exp \\
& + \sum_{m=2}^M \mathbf{1}\{\eta_i = m\} \left(\alpha^{w,\eta^m} + \sum_{j \in \mathcal{J}_\theta} \alpha^{w,\eta^m \times \theta^j} \theta_i^j \right) \text{ for } w = 14.
\end{aligned}$$

which includes grade repetition in secondary education ($delay^{se}$), secondary education diploma (hs_track^{hs}), multidimensional skills (θ^j), tertiary education enrolment and diploma (TE and TD) and work experience at age 17 (Work_Exp).²³ This functional form includes multidimensional skill complementarities, interactions between skills and tertiary enrolment, interactions between tertiary completion and secondary-school track, interactions between skills and these educational pathways, and selected type-skill interactions that allow returns to vary with unobserved heterogeneity.²⁴

The main wage outcome is therefore an early-career outcome. The estimated returns should be interpreted as returns to skills measured at age 17 and evaluated using early-career wage outcomes, not as lifecycle returns to the complete post-schooling skill stock (Lochner et al., 2025).²⁵

I include local unemployment rates as node-specific shifters in the sequential model. Their role

²³Grade retention enters the wage equation as a reduced-form control for delayed school progression, disrupted educational trajectories, and potential stigma or timing effects not fully captured by final attainment and work experience.

²⁴This includes (i) multidimensional skills, θ^j for $j \in \{cog, soc, dil\}$, (ii) skill complementarities ($\theta^{cog} \theta^{soc}$ and $\theta^{cog} \theta^{dil}$), (iii) interactions between skills and tertiary education enrolment, (iv) interactions between tertiary education diploma and secondary-school track, and (v) interactions between skills, tertiary education diploma, and secondary-school track.

²⁵The present-value wage analysis in Appendix C: Results assesses the robustness of the results to a broader earnings measure, but the benchmark estimand remains early-career returns.

is to generate variation in intermediate states, such as employment and first-job wage observation, while being excluded from later outcome equations. The corresponding exclusion restriction is that, conditional on observed histories and latent type, a local unemployment rate assigned to a given node affects subsequent outcomes only through that node. Under this maintained assumption, these shifters help identify selection into observed first-job wages and the parameters governing realised wages, as in Ashworth et al. (2021) and related literature (Heckman et al., 2018a, 2018b).²⁶

Estimation Each endogenous variable of the model is mapped to a node-specific likelihood contribution ℓ_{it}^m , conditional on the observed state variables H_{it} and the unobserved type $m \in M$. Discrete choice functions ϕ^s and ϕ^e are grouped in $\phi_{\kappa_{it}}^t$, while continuous outcome functions τ^j and f are grouped in μ_{it} . The likelihood contribution for individual i at node t is defined as:

$$\ell_{it}^m = \begin{cases} \frac{1}{\sigma_t} \varphi\left(\frac{y_{it} - \mu_t(H_{it}; \alpha^m)}{\sigma_t}\right) & \text{if } t \in T_{\text{cont}}, \\ \Psi^t(\phi_{\kappa_{it}}^t(H_{it}; \alpha^m)) & \text{if } t \in T_{\text{disc}}, \end{cases} \quad (8)$$

where $\varphi(\cdot)$ denotes the standard normal probability density function and $\Psi^t(\cdot)$ the function associated with the logit or ordered logit specification at node t . Idiosyncratic shocks for continuous outcomes are assumed to be normally distributed, $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_t^2)$, while binary and ordered outcomes follow a type I extreme value distribution. For clarity, I define $T_{\text{cont}} = \{t \in T : y_{it} \text{ is continuous}\}$ and $T_{\text{disc}} = \{t \in T : D^t(\kappa_{it}) \text{ is discrete}\}$.²⁷

When introducing unobserved heterogeneity, the likelihood is no longer separable, and the optimisation problem becomes:

$$\{\hat{\alpha}, \hat{\pi}\} = \arg \max_{\alpha, \pi} \sum_{i=1}^I \log \left[\sum_{m=1}^M \pi_m \prod_{t=1}^T \ell_{it}^m \right],$$

²⁶School recommendations and local labour-market conditions play different roles in the sequential model, as shown in Bruneel-Zupanc and Beyhum (2024). Recommendations are early, type-informative outcomes that strongly predict subsequent educational choices. Local unemployment rates provide node-specific variation in intermediate choices and wage observation. Their identifying role is model-based: conditional on observed histories and latent type, they are assumed to affect later outcomes only through the corresponding node in the sequence.

²⁷Although the likelihood is indexed by m , the type-specific parameters α^m are restricted to type intercepts and selected type-skill interactions, while slopes for observed covariates X_i are constrained to be common across types, consistent with the equations above.

where given a number of M unobserved types, I estimate both the type probabilities associated with each unobserved type m , π_m , and m -specific parameters for each outcome t . At this stage, the likelihood is no longer separable because of the correlation induced by α and π across different choices. I estimate this likelihood using the EM algorithm. Additional details on the EM algorithm are provided in Appendix B.3: Expectation-maximisation (EM) algorithm. I evaluate the model optimisation and the number of heterogeneity types in Appendix Table 26. Appendix Table 27 reports goodness-of-fit statistics for each cohort-specific model.

5 Results

Model estimates Table 4 reports the relevant coefficients from a simplified wage function, showing the difference when controlling for unobserved ability.²⁸ It compares specifications without unobserved heterogeneity and when including two and three unobserved types to the wage function. Each type is represented by a dummy variable indicating whether an individual belongs to the latent type, which is then interacted with multidimensional skills. As a result, the returns to skills are type-specific: observationally identical individuals benefit differently from the same bundle of skills depending on their unobserved type.

Unobserved types consistently capture part of the variation in skill returns.²⁹ First, types differ in baseline log hourly wages: for example, for cohort M (Z), type 2 individuals earn 9.2 (33.6) percentage points higher wages relative to type 1. Second, accounting for unobserved types changes the coefficients of multidimensional skills: in cohort M, an additional standard deviation in diligence skills yields a 6.1 percentage-point return for the baseline latent type, with returns varying substantially for other types due to unobserved heterogeneity. The estimated complementarities across skills also shift. Third, the coefficients on endogenous educational outcomes change when

²⁸Relative to the benchmark model, I estimate a model which includes the following functional form for the wage function to make the comparison of coefficients clearer in the table: $f(X, \eta, D^s, \theta^j, D^e, Z^w) = \alpha_0^w + \alpha^{w,X} X + \alpha^{w,Unem} Unem^w + \alpha^{w,delay^{se}} delay^{se} + \alpha^{w,hs} hs_track^{hs} + \alpha^{w,\theta^j} \theta^j + \alpha^{w,TE} TE + \alpha^{w,TD} TD + \eta^m (\alpha^{w,\eta^m} + \alpha^{w,\eta^m \times \theta^j} \theta^j)$. Appendix B.4: Model estimates reports the relevant coefficients from the benchmark models for each step of the sequence.

²⁹Appendix Table 26 reports model-selection statistics across alternative numbers of latent types and starting values. Although AIC and BIC favour three types, I use $M = 2$ in the baseline because the two-type likelihood is stable across starting values and supports the cross-cohort comparison of type-specific parameters; see Appendix B.3: Expectation-maximisation (EM) algorithm for a full discussion.

Table 4: Wage function cohort-specific coefficients, accounting for unobserved ability

	M (1987-1995)						Z (1996-2003)					
	Log hourly wage (first job)											
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Cognitive skills (θ^{cog})	0.038*	(0.020)	0.074***	(0.025)	0.038	(0.024)	0.060**	(0.029)	0.050	(0.033)	0.023	(0.043)
Diligence skills (θ^{dil})	0.016	(0.018)	0.061**	(0.024)	0.067***	(0.026)	-0.001	(0.025)	0.013	(0.028)	-0.012	(0.037)
Social skills (θ^{soc})	0.002	(0.018)	0.029	(0.025)	0.037	(0.025)	0.065***	(0.025)	0.051	(0.032)	-0.068*	(0.035)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	0.005	(0.018)	-0.011	(0.019)	-0.006	(0.019)	0.054**	(0.025)	0.060**	(0.026)	0.007	(0.024)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	0.001	(0.018)	-0.013	(0.019)	-0.011	(0.019)	-0.007	(0.024)	0.002	(0.027)	-0.003	(0.023)
Lower secondary education	0.063	(0.118)	0.083	(0.117)	0.098	(0.117)	0.046	(0.118)	0.029	(0.118)	-0.069	(0.103)
Intermediate secondary education	0.176	(0.115)	0.146	(0.115)	0.123	(0.115)	0.041	(0.108)	0.029	(0.108)	-0.023	(0.094)
Upper secondary education	0.300**	(0.118)	0.248**	(0.121)	0.190	(0.123)	0.091	(0.121)	0.094	(0.120)	0.102	(0.110)
Tertiary education enrollment	0.357***	(0.059)	0.368***	(0.059)	0.373***	(0.059)	0.240***	(0.077)	0.242***	(0.077)	0.278***	(0.066)
Tertiary education diploma	0.164***	(0.054)	0.162***	(0.054)	0.164***	(0.054)	0.218**	(0.085)	0.235***	(0.085)	0.117	(0.073)
Type 2			0.092**	(0.042)	-0.182***	(0.052)			0.336***	(0.098)	0.202***	(0.057)
Type 2 \times Cognitive skills (θ^{cog})			-0.070*	(0.040)	0.038	(0.043)			0.027	(0.076)	0.073	(0.054)
Type 2 \times Diligence skills (θ^{dil})			-0.069*	(0.037)	0.012	(0.045)			0.017	(0.061)	-0.063	(0.049)
Type 2 \times Social skills (θ^{soc})			-0.021	(0.036)	0.021	(0.045)			0.212***	(0.067)	0.064	(0.048)
Type 3					-0.015	(0.070)					-1.661***	(0.111)
Type 3 \times Cognitive skills (θ^{cog})					-0.002	(0.055)					-0.289***	(0.083)
Type 3 \times Diligence skills (θ^{dil})					-0.130**	(0.051)					-0.531***	(0.076)
Type 3 \times Social skills (θ^{soc})					-0.045	(0.049)					-0.012	(0.076)

NOTE.- The dependent variable is log hourly wages in the first job. Skill variables are the baseline age-17 factors constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. The coefficients are computed from a simplified model that excludes interactions between skills and endogenous choices as well as nonlinearities. Lower, intermediate, and upper secondary education refer to completed levels relative to the baseline category of dropping out from secondary education. Tertiary education includes both university and vocational colleges. Type 2 = dummy equal to 1 if the student belongs to unobserved type 2 instead of type 1. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

unobserved heterogeneity is included: in cohort M, the positive return to upper secondary education diminishes once unobserved types are included in the wage function. Similarly, for cohort Z, this happens for returns to lower and intermediate secondary education. Taken together, these results suggest that part of the returns attributed to multidimensional skills in models without accounting for unobserved types actually reflects underlying differences in unobserved ability.

This pattern reflects the model-implied correlation between unobserved ability and endogenous choices, skill development and labour market outcomes. Table 5 reports type-specific coefficients on endogenous choices and outcomes. Within each cohort, type 2 individuals are more likely to repeat a grade in secondary school and less likely to have worked before age 17. They also display weaker multidimensional skills at age 17, especially in diligence and social skills, and are less likely to pursue tertiary education. In cohort Z, they are also less likely to complete a degree. Despite these disadvantages, type 2 individuals earn higher wages in their first job, with the advantage particularly pronounced in cohort Z, where social skills directly raise wages for this type.

Table 5: Unobserved ability coefficients by cohort

Endogenous t		M (1987-1995)				Z (1996-2003)			
		Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Grade repetition (Primary education)	$\alpha^{t,2}$	-1.125***	(0.131)	-2.172***	(0.247)	-0.337**	(0.132)	-1.388***	(0.278)
	$\alpha^{t,3}$			-1.246***	(0.124)			-0.538***	(0.135)
School recommendation	$\alpha^{t,2}$	-0.161***	(0.054)	0.085	(0.089)	-0.536***	(0.067)	2.522***	(0.115)
	$\alpha^{t,3}$			0.346***	(0.070)			-0.396***	(0.071)
Grade repetition (Secondary education)	$\alpha^{t,2}$	0.949***	(0.085)	3.226***	(0.213)	0.474***	(0.094)	-0.310*	(0.181)
	$\alpha^{t,3}$			1.687***	(0.206)			0.728***	(0.095)
Secondary education enrollment	$\alpha^{t,2}$	1.601***	(0.072)	3.732***	(0.134)	0.211***	(0.071)	3.430***	(0.181)
	$\alpha^{t,3}$			1.806***	(0.089)			0.579***	(0.074)
Work experience at age 17	$\alpha^{t,2}$	-0.594***	(0.064)	-1.519***	(0.121)	-0.316***	(0.081)	-0.693***	(0.126)
	$\alpha^{t,3}$			-0.629***	(0.084)			-0.461***	(0.084)
Cognitive test available	$\alpha^{t,2}$	-0.395***	(0.064)	-0.694***	(0.115)	-0.416***	(0.072)	1.591***	(0.110)
	$\alpha^{t,3}$			-0.642***	(0.083)			-0.400***	(0.078)
Cognitive skills (θ^{cog})	$\alpha^{t,2}$	-0.462***	(0.039)	-0.773***	(0.068)	-0.072	(0.046)	0.206***	(0.060)
	$\alpha^{t,3}$			-0.280***	(0.047)			-0.145***	(0.051)
Diligence skills (θ^{dil})	$\alpha^{t,2}$	-0.818***	(0.024)	-1.805***	(0.041)	-1.030***	(0.031)	-0.669***	(0.045)
	$\alpha^{t,3}$			-0.883***	(0.030)			-1.233***	(0.031)
Social skills (θ^{soc})	$\alpha^{t,2}$	-0.946***	(0.024)	-1.915***	(0.041)	-1.415***	(0.027)	-0.428***	(0.043)
	$\alpha^{t,3}$			-0.937***	(0.030)			-1.340***	(0.030)
Secondary education diploma	$\alpha^{t,2}$	2.049***	(0.119)	4.639***	(0.224)	-0.505***	(0.138)	2.769***	(0.156)
	$\alpha^{t,3}$			2.365***	(0.134)			0.287*	(0.149)
Tertiary education enrollment	$\alpha^{t,2}$	-0.877***	(0.144)	-2.183***	(0.276)	-0.880***	(0.210)	0.088	(0.189)
	$\alpha^{t,3}$			-0.820***	(0.167)			-0.662***	(0.229)
Tertiary education diploma	$\alpha^{t,2}$	0.021	(0.217)	-0.316	(0.430)	-1.903***	(0.480)	0.162	(0.359)
	$\alpha^{t,3}$			0.000	(0.280)			-0.451	(0.491)
Wage (first job) observed	$\alpha^{t,2}$	-0.715***	(0.166)	-1.494***	(0.307)	-0.932***	(0.167)	-1.032***	(0.178)
	$\alpha^{t,3}$			-0.680***	(0.195)			-1.118***	(0.182)
Log hourly wage (first job)	$\alpha^{t,2}$	0.092**	(0.042)	0.205**	(0.089)	0.336***	(0.098)	-0.049	(0.079)
	$\alpha^{t,2} \times \theta^{cog}$	-0.070*	(0.040)	-0.014	(0.070)	0.027	(0.076)	-0.067	(0.077)
	$\alpha^{t,2} \times \theta^{dil}$	-0.069*	(0.037)	-0.128**	(0.060)	0.017	(0.061)	-0.048	(0.065)
	$\alpha^{t,2} \times \theta^{soc}$	-0.021	(0.036)	-0.049	(0.060)	0.212***	(0.067)	-0.133*	(0.069)
	$\alpha^{t,3}$			0.180***	(0.052)			0.260**	(0.105)
	$\alpha^{t,3} \times \theta^{cog}$			-0.039	(0.044)			0.136	(0.085)
	$\alpha^{t,3} \times \theta^{dil}$			-0.023	(0.045)			0.006	(0.069)
				-0.005	(0.045)			0.198***	(0.069)
Type 1 proportion		0.514		0.184		0.699		0.573	
Type 2 proportion		0.486		0.177		0.301		0.133	
Type 3 proportion				0.640				0.294	

NOTE.- This table reports, for each endogenous choice and outcome t of the model, $\alpha^{t,m}$, the estimated coefficient on a dummy variable that takes the value 1 if the student belongs to unobserved type 2 or 3 instead of type 1. For each cohort, I estimate two models: (i) with two unobserved types and (ii) with three unobserved types. The type proportion indicates the percentage of individuals classified as each type in the full sample. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Within each cohort, type 2 represents a group of individuals who earn higher wages because of unmeasured ability, despite having lower measured skills and educational attainment. Appendix B.4: Model estimates presents a set of tables reporting the relevant estimated coefficients from the sequential model at each step, separately for cohorts M and Z.

Changes across cohorts in returns to multidimensional skills I estimate direct and total returns to multidimensional skills through counterfactual simulations, separately for cohorts M (1987–1995) and Z (1996–2003). The simulations are based on the full model and therefore account for

complementarities across skills, education, and latent type.

For each individual, I compare predicted wages under the observed skill vector Θ_i with predicted wages after increasing one skill θ_i^j , for $j \in \{cog, dil, soc\}$, by one standard deviation while holding the other skill dimensions fixed.³⁰ Let Θ_i^{j+} denote this counterfactual skill vector. The direct return holds downstream educational choices fixed at their simulated baseline values. The total return allows downstream educational choices in the school-to-work phase to adjust to the higher skill level, so it includes both the direct wage effect and the indirect effect operating through educational sorting. Let $D_i^{\mathcal{E}}(\Theta)$ denote the downstream educational pathway generated by the model when individual i has skill vector Θ . In the full model,

$$D_i^{\mathcal{E}}(\Theta) = (D_i^{10}(\Theta), D_i^{11}(\Theta), D_i^{12}(\Theta)),$$

corresponding to secondary diploma, tertiary enrolment, and tertiary completion.

The direct return to skill j in cohort c is

$$\Delta_{\theta^j, c}^{\text{direct}} = \mathbb{E}_c \left[Y_i \left(\Theta_i^{j+}, D_i^{\mathcal{E}}(\Theta_i) \right) - Y_i \left(\Theta_i, D_i^{\mathcal{E}}(\Theta_i) \right) \right].$$

The total return to skill j in cohort c is

$$\Delta_{\theta^j, c}^{\text{total}} = \mathbb{E}_c \left[Y_i \left(\Theta_i^{j+}, D_i^{\mathcal{E}}(\Theta_i^{j+}) \right) - Y_i \left(\Theta_i, D_i^{\mathcal{E}}(\Theta_i) \right) \right].$$

I then compute changes in returns across cohorts as

$$\Delta_{\theta^j}^g = \Delta_{\theta^j, Z}^g - \Delta_{\theta^j, M}^g, \quad g \in \{\text{direct}, \text{total}\}.$$

These estimates are reported in Table 6.

Table 6 starts from the returns to “aggregate skills”, which refer to a σ increase in all multidimensional skills, including the effect of complementarities with other skills and latent ability. For demographic cohort M, this corresponds to a total (direct) return of 15.7% (6.1%). For cohort Z, the total (direct) return rises to 22.2% (21.1%).

³⁰All effects are expressed as the impact of a one standard deviation increase in the relevant skill.

Table 6: Wage returns to multidimensional skills by cohort: direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.157*** (0.049)	0.061 (0.049)	0.222*** (0.069)	0.211*** (0.070)	0.065* (0.038)	0.150*** (0.032)
Cognitive skills (θ^{cog})	0.107*** (0.022)	0.045** (0.022)	0.098*** (0.031)	0.061* (0.033)	-0.009 (0.019)	0.016 (0.015)
Diligence skills (θ^{dil})	0.056** (0.024)	0.028 (0.019)	0.008 (0.026)	0.009 (0.024)	-0.049** (0.020)	-0.019* (0.010)
Social skills (θ^{soc})	0.030 (0.023)	0.022 (0.018)	0.073** (0.029)	0.087*** (0.027)	0.042** (0.021)	0.065*** (0.014)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.026 (0.027)	-0.030 (0.020)	0.045 (0.032)	0.052* (0.027)	0.071*** (0.027)	0.082*** (0.010)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.012 (0.025)	-0.004 (0.019)	-0.002 (0.029)	0.002 (0.026)	0.010 (0.025)	0.005 (0.010)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.051 (0.038)	-0.017 (0.030)	-0.089* (0.046)	-0.052 (0.043)	-0.038 (0.027)	-0.035* (0.018)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Cognitive skills (θ^{cog}) yield the largest returns among multidimensional skills. In cohort M, they generate direct (total) returns of 4.5% (10.7%). In cohort Z, the corresponding returns are 6.1% (9.8%). The returns remain stable across cohorts and in both cases, the indirect channel through education is substantial: 6.2 percentage points for cohort M and 3.7 points for cohort Z (see Appendix Table 46 for a test on the difference between direct and total returns). This is consistent with higher education sorting being an important channel for returns to cognitive skills (Heckman et al., 2006; Edin et al., 2022).

Returns to diligence skills (θ^{dil}) are significant only for cohort M, where they contribute about 5.6 percentage points as total return. By contrast, social skills show no significant effect for cohort M, but they gain substantial importance for cohort Z: a σ increase in social skills translates to an increase in total (direct) returns of 4.2 (6.5) percentage points. Most of this effect operates

through the direct channel. This shift can be interpreted as consistent with changing labour market valuation of social skills (Deming, 2017), rather than a change in the way individuals sort into higher education.

Which skills yield higher (or lower) returns? Cognitive skills remain stable over time, with no significant changes across cohorts. By contrast, social skills have gained importance, while diligence skills have lost relevance. Specifically, the direct (total) returns to social skills increased by 6.5 (4.2) percentage points, consistent with Deming (2017), whereas diligence skills show a decline of 1.9 (4.9) percentage points.

A key advantage of this approach is that it separates direct and total returns to skills. For social skills, the increase is mainly direct: direct returns rise by 6.5 percentage points, while total returns rise by 4.2 percentage points. By contrast, the decline in diligence returns operates mainly through educational sorting. Total returns to diligence decline by about 4.9 percentage points, whereas direct returns decline by only 1.9 percentage points. This pattern suggests that social skills became more rewarded in the labour market, while the role of diligence weakened primarily through its declining association with higher education sorting (see Appendix Table 47 for evidence on educational sorting). This distinction would be missed in specifications that treat education only as a control.

It is important to note that the benchmark analysis does not model the potential development of skills during the school-to-work transition phase, that is, after skills are measured at age 17 in the GSOEP. The estimated returns should therefore be interpreted as returns to skills measured at age 17, evaluated using early-career wage outcomes (Deming, 2017; Edin et al., 2022; Izadi and Tuhkuri, 2026). In the robustness checks, I assess this concern using the limited GSOEP subsample with later skill measurements.

Changes in complementarities and heterogeneous returns by skill bundle Table 6 highlights an important shift in the returns to multidimensional skills: the changing role of complementarities. For instance, complementarities between cognitive and diligence skills increase across cohorts. As a result, the average changes in returns reported in Table 6 may mask substantial heterogeneity across multidimensional skill bundles.

Using counterfactual simulations, Table 7 reports returns to an additional standard deviation in

a non-cognitive skill θ^j , for $j \in \{soc, dil\}$, conditional on selected multidimensional skill bundles. For cohort $c \in \{M, Z\}$ and $g \in \{direct, total\}$, define the bundle-specific return as

$$\Delta_{\theta^j, c}^g(\theta^{cog}, \theta^j) = \mathbb{E}_c \left[\Delta_{\theta^j}^g \mid \theta^{cog}, \theta^j \right]. \quad (9)$$

The change in this return across cohorts is then

$$E[\Delta_{\theta^j}^g \mid \theta^{cog}, \theta^j] = E[\Delta_{\theta^j, Z}^g - \Delta_{\theta^j, M}^g \mid \theta^{cog}, \theta^j] \quad \text{for } g \in \{direct, total\} \text{ and } j \in \{soc, dil\}, \quad (10)$$

where I focus on skill bundles that include low ($\theta^{cog} = -1$) or high ($\theta^{cog} = 1$) levels of cognitive skills.³¹ Table 7 reports four multidimensional skill bundles: high and low cognitive skills, each combined with high and low levels of non-cognitive skill $j \in \{soc, dil\}$. For each cohort, Table 7 includes direct and total returns, together with the changes across cohorts conditional on these different bundles. Appendix Table 42 includes multidimensional skill bundles with $\theta^j = -2$ and $\theta^j = 2$.

While Table 6 reports an average decline in total returns to diligence of 4.9 percentage points, Table 7 shows that this decline is concentrated among individuals with low cognitive skills. For this group, the decline is about 10 percentage points, and it reaches about 12 percentage points among individuals with above-average diligence. By contrast, individuals with high social skills experience an increase in total returns to social skills across cohorts, regardless of their level of cognitive skills. Direct returns display a similar pattern: returns to social skills rise broadly across the distribution, while the decline in returns to diligence is concentrated among low-cognitive individuals.

The pattern for diligence differs again by cognitive ability. Low-cognitive individuals face a pronounced drop in direct returns to diligence, whereas high-cognitive individuals experience a large and positive increase. These results are stronger when considering individuals whose cognitive skills are two standard deviations above or below the mean. Appendix Table 42 shows that, among low-cognitive individuals, the decline in total returns to diligence ranges from 17.7 to 19.1 percentage points, while the decline in direct returns is about 18 percentage points.

There are also large increases in the direct returns to social skills and diligence skills among

³¹In this simulation, I set the remaining non-cognitive skill equal to zero, corresponding to the sample mean.

Table 7: Changes in returns to one standard deviation increase in multidimensional skills across cohorts by skill bundle

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Z (1996-2003)	Changes across cohorts	M (1987-1995)	Z (1996-2003)	Changes across cohorts
Cognitive (θ^{cog}) \times Social (θ^{soc})							
$\theta^{cog} = -1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	0.039 (0.030)	0.074** (0.033)	0.034 (0.021)	0.026 (0.027)	0.086*** (0.032)	0.060*** (0.012)
$\theta^{cog} = -1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	0.034 (0.032)	0.075** (0.034)	0.042 (0.026)	0.026 (0.027)	0.086*** (0.032)	0.060*** (0.012)
$\theta^{cog} = 1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	0.031 (0.028)	0.072 (0.044)	0.041 (0.029)	0.019 (0.026)	0.089** (0.044)	0.071*** (0.023)
$\theta^{cog} = 1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	0.016 (0.026)	0.072 (0.045)	0.056* (0.033)	0.019 (0.026)	0.089** (0.044)	0.071*** (0.023)
Cognitive (θ^{cog}) \times Diligence (θ^{dil})							
$\theta^{cog} = -1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.078*** (0.029)	-0.030 (0.033)	-0.108*** (0.018)	0.062** (0.026)	-0.035 (0.029)	-0.098*** (0.007)
$\theta^{cog} = -1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.089*** (0.032)	-0.029 (0.032)	-0.119*** (0.021)	0.062** (0.026)	-0.035 (0.029)	-0.098*** (0.007)
$\theta^{cog} = 1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.033 (0.031)	0.060 (0.046)	0.027 (0.026)	0.002 (0.029)	0.069 (0.044)	0.067*** (0.020)
$\theta^{cog} = 1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.041 (0.032)	0.060 (0.046)	0.018 (0.031)	0.002 (0.029)	0.069 (0.044)	0.067*** (0.020)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Skill bundles fix these standardized factor scores at the values shown in the first column; returns to $\theta^{soc} + 1$ or $\theta^{dil} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

high-cognitive individuals. This heterogeneity is central for interpreting the average return to diligence in Table 6. The average direct return to diligence declines by only 1.9 percentage points and is only marginally significant, but this estimate conceals a much larger decline among low-cognitive individuals. For this group, the direct return to diligence falls by 9.8 percentage points. This decline is partly offset by an increase in the return to diligence among high-cognitive individuals. Hence, the average effect masks a divergence across skill bundles: diligence loses value when combined with low cognitive skills, but not when combined with high cognitive skills.

Therefore, I further examine whether the average cohort changes mask heterogeneity across the skill distribution. In Appendix Section C.2: Distributional treatment effects, I re-estimate the wage equation with a third-order polynomial in the multidimensional skill vector and its complementarities, and then compute model-implied returns at different skill bundles. The results show that the decline in returns to diligence is concentrated among low-cognitive individuals across most of the diligence distribution. By contrast, the increase in returns to social skills is largest among individuals with above-average cognitive and social skills. These patterns reinforce the interpretation that

the fall in returns to diligence is consistent with the declining value of routine-task comparative advantage, while the rise in returns to social skills reflects stronger complementarities between social and cognitive skills (Deming, 2017).

Overall, the evidence points to a clear shift in Germany across recent cohorts: a stark decline in returns to diligence skills driven by low-cognitive individuals, even after controlling for observed characteristics, endogenous educational choices, and unobserved ability. This pattern holds for both total and direct returns. At the same time, individuals with high cognitive and high social skills experience a substantial increase in returns to social skills.

6 Changes in the task content of occupations

This pattern might be consistent with a demand-side interpretation: diligence may have been rewarded in routine-intensive occupations, but this advantage may have weakened as the share of routine-task-intensive occupations declined in the German labour market.

This section provides supporting evidence for this interpretation. Following the task-based framework in Acemoglu and Autor (2011), I view skills as productive inputs whose value depends on the tasks workers perform. If high-diligence workers sort disproportionately into routine-intensive occupations, then deroutinisation should reduce the return to diligence, especially for low-cognitive workers with fewer margins to move into cognitive- or social-task intensive jobs.

I examine this channel in two steps using data from ESCO (see Appendix A.2: ESCO for a detailed description of the dataset). First, I document how the task content of occupations in Germany changed between 1984 and 2020.³² Second, I estimate whether age-17 skills predict sorting into occupations intensive in routine, social, or non-routine analytical tasks.

6.1 Mechanism and empirical predictions

The evolution of task demand yields three empirical predictions, following Acemoglu and Autor (2011). First, if social-task-intensive occupations become more important, the relative return to social skills should increase. Second, if non-routine analytical task demand remains broadly stable,

³²Given the panel structure of the GSOEP, I retain the last available occupational observation for each individual within each half-decade between 1984 and 2020, so that each individual contributes at most one observation per half-decade.

the return to cognitive skills should change little. Third, if routine-task demand declines, the return to diligence should fall, particularly for workers whose skill bundles lead them to sort into routine-intensive occupations. This last prediction is central for interpreting the decline in returns to diligence among low-cognitive individuals.³³

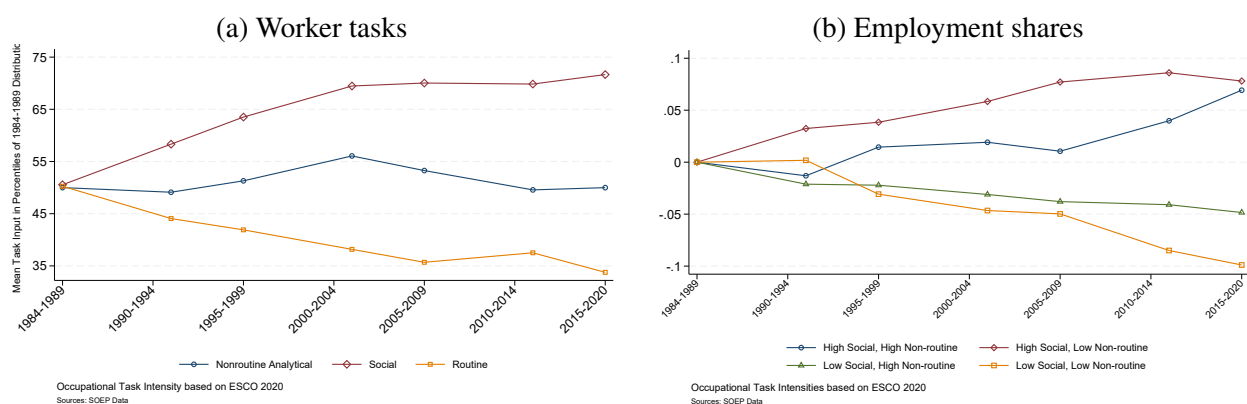
Individuals with stronger social skills are expected to have a comparative advantage in occupations intensive in social tasks (Deming, 2017). Individuals with stronger cognitive skills are expected to have a comparative advantage in occupations intensive in non-routine analytical (cognitive) tasks. By contrast, diligence skills are likely to be especially valuable in occupations with a stronger routine component, where reliability, effort, and compliance are highly rewarded (Bowles and Gintis, 2002; Heckman et al., 2006). Indeed, there is evidence that employers in unskilled labour markets value dependability, and persistence more than cognitive ability (Bowles and Gintis, 2002; Heckman et al., 2006). For this reason, routine-intensive jobs may have rewarded diligence more strongly, especially among workers with lower cognitive skills.

Changes in the task content Plot (a) of Figure 4 replicates both Figure I from Autor et al. (2003) and Figure III from Deming (2017) using data from the GSOEP and the ESCO. Following Deming (2017) closely, I ensure that each task measure variable has a mean of 50 centiles in 1984 and that the data are aggregated to the industry-education-sex level. This aggregation controls for changes in the industry and labour supply in the German economy. Subsequent movements should be interpreted as changes in the employment-weighted mean of each task relative to its importance in 1984.

Overall, social-task-intensive occupations became substantially more important in Germany between 1984 and 2020. Over the same period, the employment-weighted index of routine tasks declined by about 30 percent relative to its 1984 baseline. This shift away from routine work mirrors the growing importance of social tasks and is comparable to the pattern documented for the United States by Deming (2017). Non-routine analytical task intensity increased until the early

³³Acemoglu and Autor (2011) consider a technological change that raises the productivity of high-skill workers in all tasks. The model's output is that high-skill workers would now perform some tasks formerly performed by middle-skilled workers. Relative wages paid to workers performing these (once) "middle-skill" tasks would increase since more productive high-skill workers now perform them. However, their analysis shows that the relative wages of medium-skill workers formerly performing these tasks would fall. This paper does not consider measures of low to high-skilled workers but workers with a bundle of multidimensional skills. The results are intuitively similar: e.g. individuals with high social skills have a comparative advantage in performing occupations intensive in social tasks.

Figure 4: Task trends and employment-share changes in Germany (1984–2020)



NOTE.— Panel (a) is constructed to parallel Figure I of Autor et al. (2003) and Figure III of Deming (2017), using data from Germany. Data are aggregated to industry-education-sex cells by year, and each cell is assigned a value corresponding to its rank in the 1984 distribution of task input. Each task measure variable has a mean of 50 centiles in 1984. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year. Panel (b) plots the change in employment share (relative to a 1984 baseline) between 1984 and 2020 for occupations that are above and/or below the 50th percentile in non-routine analytical and social skill task intensity as measured by ESCO for the German economy.

2000s but subsequently declined and stabilised close to its 1984 level. This evolution is consistent with the decline in non-routine analytical task demand documented by Beaudry et al. (2016) for the United States after the early 2000s.

Panel (b) of Figure 4 shows that the employment share of occupations intensive in social tasks increased substantially, regardless of their non-routine analytical task content.³⁴ By contrast, the employment share of occupations with low social and low cognitive task intensity declined. This shift is important in this setting because it occurred between the early 2000s and the post-2010 period, which roughly separates the two birth cohorts analysed in the paper. Appendix Figure 10 shows that the pattern is robust to using continuous ESCO measures and alternative task measures from O*NET.

6.2 Skills and tasks

The task trends above suggest that occupational sorting is one plausible channel through which changes in task demand may be reflected in skill returns. In the task-based framework of Acemoglu and Autor (2011), workers whose skill bundles are most productive in declining routine tasks may

³⁴I control for possible skill upgrading by dividing occupations into four categories based on whether they are above or below the median percentile in both non-routine analytical (cognitive) and social skill task intensity (see also Deming, 2017). In Deming, 2017, possible skill upgrading may be the result of the high correlation between social and non-routine analytical (cognitive) skills task measures.

experience lower relative returns as the demand for those tasks falls.

I therefore estimate whether multidimensional skills at age 17 predict sorting into occupations with different task content. Using the task measures extracted from ESCO, I classify each occupation with three binary indicators equal to one if its social, routine, or non-routine analytical task content is above the 50th percentile. I then re-estimate the sequential model using each task-content indicator as the outcome in place of log hourly wages. To this end, I add three new equations, indexed by $o \in O = \{S, R, C\}$, with the following functional form:

$$\begin{aligned}
 f^o(X, \eta, D^s, \theta^j, D^e, Z^o) = & \alpha_0^o + \alpha^{o,X} X + \alpha^{o,Unem} Unem^o + \alpha^{o,delay^{se}} delay^{se} \\
 & + \alpha^{o,we} Work_exp + \alpha^{o,hs} hs_track^{hs} + \alpha^{o,\theta^j} \theta^j \\
 & + \alpha^{o,TE} TE + \alpha^{o,TD} TD \\
 & + \alpha^{o,\eta^m} \eta^m \text{ for } o \in O = \{S, R, C\},
 \end{aligned}$$

where the function is simplified relative to the log-wage equation. I use this model to estimate how a one standard deviation increase in each skill θ^j , for $j \in \{cog, soc, dil\}$, affects the probability of sorting into occupations intensive in social, routine, or non-routine analytical tasks. Each task outcome O_{ts} , for $ts \in \{S, R, C\}$, is a binary indicator equal to one if the occupation is above the 50th percentile in the corresponding task dimension (see Appendix Table 60 for a robustness check using occupation above the 75th percentile).

The results are consistent with the proposed demand-side interpretation. Cognitive skills strongly predict sorting into non-routine analytical occupations, while social skills predict sorting into social-task-intensive occupations. Diligence skills also predict sorting into routine-intensive occupations: a one standard deviation increase in diligence raises the probability of working in a routine-intensive occupation by 1.4 percentage points. This relationship remains after accounting for observed characteristics, endogenous educational choices, work experience, and latent type. Combined with the decline in routine-task demand documented above, this sorting pattern is consistent with the decline in returns to diligence across cohorts, especially among low-cognitive individuals.

Table 8: Effects of one standard deviation increase in multidimensional skills on occupational sorting

	Occupational task content sorting:		
	Social task	Routine task	Cognitive task
Cognitive skills (θ^{cog})	0.010*** (0.004)	-0.002 (0.004)	0.064*** (0.005)
Diligence skills (θ^{dil})	0.021*** (0.004)	0.014*** (0.004)	0.075*** (0.004)
Social skills (θ^{soc})	0.025*** (0.004)	0.007* (0.004)	0.081*** (0.005)

NOTE.- Each occupation is classified with a binary indicator equal to one if its task content is above the 50th percentile in the social, routine, or non-routine analytical (cognitive) dimension. The model is re-estimated using these three binary outcomes in place of starting wages. Entries report the change in the probability of sorting into the corresponding task-intensive occupation associated with a one standard deviation (σ) increase in skills. Standard errors across simulation draws are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

7 Robustness checks

This section assesses whether the main findings depend on the measurement of skills, the specification of unobserved heterogeneity, the wage outcome, the cohort definition, or the construction of task measures.

Simplified model As a first robustness check, I re-estimate changes in returns using the simplified sequential model introduced in Section 4.1. Appendix Tables 44 and 54 show that the central patterns are preserved. Cognitive-skill returns remain stable across cohorts. Social skills become more valuable, with total and direct returns increasing by 8.0 and 6.9 percentage points, respectively. The average decline in diligence returns is weaker in this specification, but the heterogeneous pattern by skill bundle remains strong. Among individuals with low cognitive skills, the return to diligence falls by about 11–12 percentage points across cohorts, both for total and direct returns. By contrast, high-cognitive individuals experience positive changes in the return to diligence. The simplified model therefore confirms the main results. These results are further compared to other specifications in Table 10.

Multidimensional skill factors The main results are robust to alternative constructions of the multidimensional skill factors. Table 9 reports the relevant wage-function coefficients from the benchmark specification and from three alternative specifications that use different skill measures, as described in Appendix Table 17.³⁵

Table 9: Wage function by cohort with robust skill factors

	Benchmark				Robust 1				Robust 2				Robust 3			
	M (1987-1995)		Z (1996-2003)		M (1987-1995)		Z (1996-2003)		M (1987-1995)		Z (1996-2003)		M (1987-1995)		Z (1996-2003)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Cognitive skills (θ^{cog})	0.064*	(0.035)	0.053	(0.039)	-0.007	(0.040)	0.039	(0.038)	-0.001	(0.040)	0.037	(0.038)	0.023	(0.038)	0.058	(0.039)
Diligence skills (θ^{dil})	0.019	(0.036)	0.006	(0.035)	-0.051	(0.035)	0.008	(0.035)	-0.055	(0.036)	-0.005	(0.034)	-0.049	(0.043)	0.004	(0.045)
Social skills (θ^{soc})	0.030	(0.035)	0.053	(0.039)	0.026	(0.037)	0.055	(0.039)	0.026	(0.038)	0.052	(0.037)	-0.022	(0.045)	0.004	(0.048)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.028	(0.020)	0.054**	(0.027)	-0.030	(0.020)	0.052*	(0.027)	-0.030	(0.019)	0.051**	(0.026)	-0.037	(0.025)	0.083**	(0.034)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.005	(0.021)	0.001	(0.029)	-0.005	(0.021)	0.003	(0.029)	0.002	(0.020)	0.003	(0.028)	0.014	(0.026)	-0.020	(0.037)
Lower secondary education	0.130	(0.121)	0.021	(0.122)	0.131	(0.121)	0.014	(0.123)	0.133	(0.121)	0.016	(0.123)	0.140	(0.122)	0.005	(0.123)
Intermediate secondary education	0.136	(0.116)	0.021	(0.108)	0.139	(0.116)	0.022	(0.108)	0.143	(0.116)	0.024	(0.108)	0.149	(0.117)	0.008	(0.109)
Upper secondary education	0.209*	(0.126)	0.143	(0.124)	0.216*	(0.126)	0.147	(0.124)	0.221*	(0.126)	0.156	(0.124)	0.227*	(0.128)	0.127	(0.124)
Tertiary education enrollment	0.407***	(0.071)	0.224***	(0.084)	0.404***	(0.071)	0.224***	(0.083)	0.403***	(0.069)	0.236***	(0.086)	0.407***	(0.071)	0.224***	(0.082)
Tertiary education diploma	0.039	(0.112)	0.281*	(0.164)	0.044	(0.111)	0.286*	(0.163)	0.051	(0.112)	0.266	(0.163)	0.031	(0.112)	0.268	(0.164)
Type 2	0.116***	(0.042)	0.304***	(0.099)	-0.106**	(0.042)	0.307***	(0.098)	-0.086**	(0.041)	0.302***	(0.097)	-0.079*	(0.041)	0.134	(0.103)
Type 2 \times Cognitive skills (θ^{cog})	-0.068*	(0.040)	-0.004	(0.077)	0.073*	(0.040)	0.010	(0.076)	0.066*	(0.039)	0.033	(0.075)	0.020	(0.037)	-0.040	(0.078)
Type 2 \times Diligence skills (θ^{dil})	-0.070*	(0.038)	0.019	(0.062)	0.070*	(0.037)	0.015	(0.061)	0.066*	(0.037)	0.019	(0.062)	0.110**	(0.046)	0.095	(0.070)
Type 2 \times Social skills (θ^{soc})	-0.002	(0.037)	0.203***	(0.067)	0.002	(0.037)	0.199***	(0.068)	0.001	(0.037)	0.196***	(0.068)	0.025	(0.046)	0.181**	(0.082)

NOTE.- The dependent variable is log hourly wages in the first job. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. Benchmark uses the baseline age-17 factors constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Robust 1 replaces the cognitive factor with a cognitive-test-only factor. Robust 2 uses the same cognitive-test-only item set, standardizes the latent cognitive factor within each age-17 survey year, and then restandardizes it in the full sample. Robust 3 uses the baseline cognitive factor and replaces the baseline non-cognitive two-factor system with dedicated social and diligence factors. Lower, intermediate, and upper secondary education refer to completed levels relative to the baseline category of dropping out from secondary education. Tertiary education includes both university and vocational colleges. Type 2 = dummy equal to 1 if the student belongs to unobserved type 2 instead of type 1. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

The three robustness specifications vary the measurement of cognitive and non-cognitive skills. Robust 1 uses only cognitive test-score measures administered in the SOEP and excludes all other variables from the cognitive factor. Robust 2 uses the same cognitive measures as Robust 1, but follows Izadi and Tuhkuri (2026) by standardising the latent factor within survey year at age 17 and then re-standardising it in the full sample. Robust 3 replaces the orthogonal non-cognitive factors with dedicated measures of diligence and social skills.

Across these specifications, the wage-function coefficients remain stable. In particular, the coefficients on unobserved types and their interactions with skills change little when the model is re-estimated with alternative skill factors. This stability suggests that the estimation is not driven by a particular measurement system for skills. For example, the coefficient on unobserved type 2

³⁵Figure 7 shows that the alternative cognitive skill factors are highly correlated.

in cohort M ranges from 0.079 to 0.116 in absolute value,³⁶ while in cohort Z it remains close to 0.30 across specifications, except for Robust 3. The interaction patterns are also stable, with cohort Z consistently showing strong complementarities between unobserved type 2 and social skills.

Table 10: Robustness of changes in skill returns

Specification	Changes in θ^{soc}		Changes in θ^{dil}		Changes in θ^{dil} for $\theta^{cog} = -1$	
	Total	Direct	Total	Direct	Total	Direct
Benchmark	0.042** (0.021)	0.065*** (0.014)	-0.049** (0.020)	-0.019* (0.010)	-0.119*** (0.021)	-0.098*** (0.007)
Robust 1	0.043 (0.027)	0.068*** (0.021)	-0.049** (0.023)	-0.017 (0.016)	-0.120*** (0.025)	-0.097*** (0.016)
Robust 2	0.040 (0.027)	0.066*** (0.021)	-0.049** (0.022)	-0.017 (0.016)	-0.122*** (0.026)	-0.098*** (0.018)
Robust 3	0.035 (0.027)	0.042* (0.024)	-0.064*** (0.024)	-0.033* (0.018)	-0.177*** (0.028)	-0.146*** (0.018)
Three unobserved types	0.030 (0.022)	0.038** (0.017)	-0.079*** (0.021)	-0.058*** (0.014)	-0.147*** (0.022)	-0.130*** (0.016)
Measurement-invariant factors	0.066* (0.035)	0.044 (0.030)	-0.013 (0.043)	-0.004 (0.037)	-0.089** (0.045)	-0.087** (0.038)
Big Five	0.080*** (0.023)	0.075*** (0.015)	-0.020 (0.026)	-0.007 (0.019)	-0.078*** (0.028)	-0.059*** (0.018)
Simplified model	0.080*** (0.014)	0.069*** (0.013)	-0.003 (0.011)	-0.018* (0.010)	-0.107*** (0.013)	-0.120*** (0.009)

NOTE.—The table reports changes across cohorts (Z minus M) in returns to log hourly wages in the first job. “Changes in θ^{soc} ” and “Changes in θ^{dil} ” refer to cohort changes in the return to a one standard deviation increase in social and diligence skills, respectively. “Changes in θ^{dil} for $\theta^{cog} = -1$ ” reports the cohort change in the return to increasing diligence by one standard deviation for individuals fixed at low cognitive skill ($\theta^{cog} = -1$) and high diligence ($\theta^{dil} = 1$). Simulation standard errors are in parentheses. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Benchmark uses the baseline age-17 factors. Robust 1 replaces the cognitive factor with a cognitive-test-only factor. Robust 2 uses the same cognitive-test-only item set as Robust 1, standardises it within each age-17 survey year, and then re-standardises it in the full sample. Robust 3 uses dedicated social and diligence factors. The three unobserved types row estimates the baseline measurement system with three unobserved types. Measurement-invariant factors impose equal cognitive-factor loadings across cohorts; Big Five replaces social and diligence with extroversion and conscientiousness; the simplified model keeps only the higher-education completion channel. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 10 summarises the main robustness checks by reporting changes in total and direct returns across cohorts for alternative measurement systems and model specifications. The results closely match the benchmark estimates. For Robust 2, which constructs skill factors following Izadi and Tuhkuri (2026), total returns to diligence skills decline by 4.9 percentage points, while direct returns to social skills increase by 6.6 percentage points (see also Appendix Table 49). Robust 1 and Robust 3 yield the same pattern: total returns to diligence skills decline respectively by 4.9

³⁶I report absolute values because, with two unobserved types, switching the type labels changes the sign but not the economic interpretation.

and 6.4 percentage points, direct returns to social skills increase by 6.8 and 4.2 percentage points (see Appendix Tables 48 and 50 for the complete set of results).

Appendix Table 52 provides an additional check using the two Big Five traits most closely related to the baseline non-cognitive factors: conscientiousness for diligence and extraversion for social skills. The results are in line with the baseline specification. While total returns to conscientiousness decline by 2 percentage points (not statistically significant), direct returns to extraversion increase by 7.5 percentage points, and the complementarity between cognitive skills and conscientiousness increases by 7.2 percentage points in total returns. Appendix Table 43 further shows that the cohort changes in returns by skill bundle are preserved when these Big Five traits are used as proxies. In particular, individuals with low cognitive skills experience a decline in both total and direct returns to conscientiousness, consistent with the role of these non-cognitive factors in sorting into routine-intensive occupations.

Appendix Tables 41 and 51 report estimates based on measurement-invariant cognitive and non-cognitive skill factors. The decline in returns to diligence skills is weaker in this specification (-1.3 percentage points), but the increase in direct returns to social skills remains positive, at 4.4 percentage points. While these coefficients are not statistically significant, they point into the same direction of the baseline estimates. On the other side, the cohort changes in returns by skill bundle are preserved: individuals with low cognitive skills experience a decline in both total and direct returns to diligence skills (-8.9 and -8.7 percentage points, respectively). These estimates provide the main check that the results are not mainly driven by the pooled baseline normalisation and show that the central patterns are preserved when the skill factors are constructed from comparable measurement systems.

Finally, the results are also robust to allowing for three unobserved types. Appendix Table 53 shows that the decline in returns to diligence skills is larger in this specification, reaching 7.9 percentage points for total returns and 5.8 percentage points for direct returns. The increase in direct returns to social skills is smaller, at 3.8 percentage points, but the complementarity between cognitive and diligence skills increases by 7.6 percentage points.

Present value of earnings and cohort definition The benchmark analysis focuses on starting wages to avoid confounding skill returns with differential work experience accumulation and on-

the-job training. As a robustness check, I compute the adjusted present value of earnings using all available wage observations for each individual. Appendix Table 57 reports direct and total returns from a one standard deviation increase in each skill, together with changes across cohorts. The decline in returns to diligence remains large, at about 12.6 percentage points. The estimates for cognitive skills are similar to the benchmark results, while the increase in returns to social skills is weaker. This difference may reflect variation in observed work experience and attrition, since individuals are not observed for the same number of post-entry years. Overall, the decline in returns to diligence is robust to using a broader earnings measure.

The cohort cut-off is another potential concern. To ensure the robustness of my results, I exclude individuals from the years that fall on the boundaries of the demographic cohort definition. Therefore, I exclude individuals born in 1994, 1995, and 1996. Table 56 in Appendix includes the results with excluded individuals. The results again show a large increase in the direct returns to social skills (6.4 percentage points) and a decline in the total returns to diligence skills (4.3 percentage points). Finally, there is a similar rise in the complementarities between cognitive and diligence skills (8.2 percentage points).

As an additional check, I address the concern that tertiary education outcomes may be right-censored for the youngest individuals in cohort *Z*, who are observed only through 2020. I therefore re-estimate the benchmark model leaving cohort *M* unchanged and restricting cohort *Z* to individuals born between 1996 and 1998. Appendix Tables 45 and 55 report the results. The increase in direct returns to social skills remains very similar to the baseline, at 6.5 percentage points. The average decline in total returns to diligence is smaller and not statistically significant in the trimmed sample. However, the main heterogeneous pattern remains: among individuals with low cognitive skills, returns to diligence decline by 8.1–9.5 percentage points in total returns and by 9.3 percentage points in direct returns. Thus, right-censoring among the youngest *Z* cohorts does not appear to drive the central distributional result that the decline in returns to diligence is concentrated among low-cognitive individuals.

Multidimensional skills development Since my analysis does not account for the potential dynamic development of skills during the school-to-work transition phase (see Figure 3), the estimated returns should be interpreted strictly as returns to skills measured at age 17 (Lochner et al.,

2025). This interpretation holds unless one assumes that skill development after age 18 is minimal and that age-17 skill levels serve as a reliable proxy for skill endowments at labour market entry. To assess the robustness of this assumption, I conduct a check on post-17 skill development based on college choices. Using a limited subsample of the GSOEP, I construct new measures of multidimensional skills observed both at age 17 and after the completion of tertiary education in Germany. Table 59 in Appendix reports the effects of higher tertiary education enrolment and graduation on rank differences in skills between age 17 and post-college measurement. While higher education is associated with higher absolute levels of multidimensional skills (see Appendix Table 58), it does not significantly alter the relative ranking of individuals based on these skills. In other words, an individual who was two standard deviations above the mean at age 17 remains similarly ranked after completing college.

8 Conclusions

This paper studies how the returns to multidimensional skills changed across recent German cohorts and through which channels. I develop a sequential model of multidimensional skills, educational choices, and early-career wages that separates direct labour market returns from total returns through higher education sorting, while accounting for persistent unobserved heterogeneity. This distinction matters because skills measured at age 17 depend on earlier investments and latent endowments, and because higher education is both an outcome of skills and a channel through which skills affect wages (Heckman et al., 2018a).

I present three main findings. First, social skills in Germany became more valuable across cohorts: the direct return to a one standard deviation increase in social skills rises by about 6 percentage points. Second, total returns to diligence skills decline by about 5 percentage points, reflecting a weakening link between diligence and higher education sorting. Third, this average decline masks substantial heterogeneity. Among individuals with low cognitive skills, returns to diligence fall by about 10 percentage points, while high-cognitive individuals are partly protected by stronger complementarities between cognitive and diligence skills.

These patterns are consistent with a demand-side interpretation. Using ESCO-based measures of occupational task content, I document a shift toward occupations intensive in social tasks and

away from routine-intensive occupations. I also show that higher diligence predicts sorting into routine-intensive occupations. This evidence supports the interpretation that routine-task displacement reduced the value of diligence for workers whose skill bundles were most strongly aligned with routine work.

The broader implication is that the returns to non-cognitive skills cannot be summarized by a single average effect. The same skill may gain or lose value depending on the worker's cognitive skills, the education channel through which the skill operates, and the tasks performed in the occupations into which workers sort. This helps reconcile the rising value of social skills with the declining value of diligence for low-cognitive workers.

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A: Data

A.1: GSOEP The analysis uses the GSOEP, a representative longitudinal household survey that has followed individuals and households in Germany since 1984 (Wagner et al., 2007; Humphries & Kosse, 2017).

The key source for measuring skills is the GSOEP Youth questionnaire, administered at age 17 since 2000. It records education, aspirations, personality traits, and related non-cognitive measures. Since 2004, corresponding to individuals born in 1987 or later, the Youth questionnaire can be linked to the COGDJ cognitive test module, which includes a short version of the I-S-T 2000 test designed for the panel setting.

The Youth questionnaire contains 9,361 respondents who can be linked to subsequent individual and household surveys. These links yield 125,728 individual-year observations, including 59,188 post-age-17 household-survey observations. Cognitive test scores are available for 4,055 Youth respondents born between 1987 and 2003. After imposing the item-availability restrictions required to construct the baseline cognitive factor, cognitive skill scores are available for 3,560 individuals. Non-cognitive skill measures are available for the broader Youth sample, while starting wages are observed for 2,219 individuals in the benchmark wage sample. Because cognitive-test availability and wage observation are not random, Table 11 compares observed characteristics by test availability, and the empirical model includes selection equations for cognitive-test participation and wage observation.

Demographic cohorts I divide the estimation sample into two cohorts: cohort *M*, born between 1987 and 1995, and cohort *Z*, born between 1996 and 2003. The cut-off separates respondents who entered adolescence before the rapid diffusion of digital technologies from those who did so afterward, which is consistent with common descriptions of Millennials and Generation Z (see Figure 5).³⁷ As a robustness check, I re-estimate the model excluding individuals born close to the cut-off, namely those born in 1994, 1995, and 1996.

³⁷See, for example, the Pew Research Center report on Generation Z: Generation Z report.

Figure 5: Internet Use across Cohorts (OECD Data)

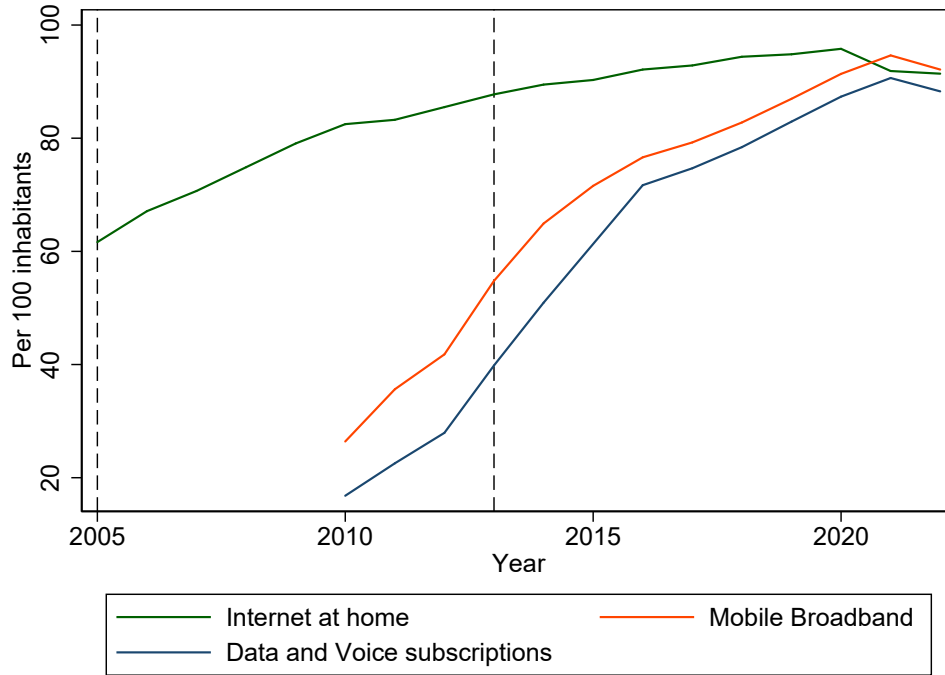


Table 11: Exogenous variables by cognitive-test availability

	(1)				(2)			
	M (1987-1995)				Z (1996-2003)			
	Mean c	Mean n	Diff.	p-value	Mean c	Mean n	Diff.	p-value
Sex	0.504	0.483	0.021	0.148	0.504	0.486	0.018	0.240
Migration Background	0.231	0.220	0.010	0.404	0.302	0.386	-0.085***	0.000
Born in Germany	0.925	0.964	-0.039***	0.000	0.841	0.897	-0.057***	0.000
Siblings	1.609	1.646	-0.037	0.344	1.399	1.578	-0.179***	0.000
Birth Year	1988.192	1990.585	-2.393***	0.000	1999.556	1999.170	0.386***	0.000
Father Upper Secondary Education	0.184	0.213	-0.029*	0.011	0.185	0.171	0.014	0.228
Mother Upper Secondary Education	0.164	0.196	-0.032**	0.004	0.181	0.171	0.011	0.365
Father University	0.147	0.167	-0.019	0.067	0.143	0.137	0.007	0.542
Mother University	0.108	0.102	0.006	0.523	0.105	0.131	-0.026**	0.009
Father High-Skilled Occupation	0.482	0.524	-0.042**	0.004	0.375	0.419	-0.044**	0.004
Mother High-Skilled Occupation	0.350	0.360	-0.010	0.485	0.315	0.361	-0.046**	0.001
Big or middle-sized city	0.407	0.386	0.022	0.127	0.326	0.352	-0.026	0.073
West Germany	0.788	0.802	-0.014	0.232	0.830	0.850	-0.021	0.070
Observations	4,931				4,430			

NOTE.— The table compares observed characteristics by cognitive-test availability, separately by cohort. Cohort *M* includes individuals born between 1987 and 1995, and cohort *Z* includes individuals born between 1996 and 2003. “Mean c” is the mean among individuals with a completed cognitive test, while “Mean n” is the mean among individuals without a completed cognitive test. The “Diff.” column reports the difference between these two means (Mean c minus Mean n). Cognitive-test availability is defined from the COGDJ module of the SOEP Youth questionnaire. The *p*-value is from a two-sample test of equality of means.

Table 12: Endogenous variables, by cohort

	Full sample			M (1987-1995)			Z (1996-2003)		
	Observed values	Mean	SD	Observed values	Mean	SD	Observed values	Mean	SD
Grade repetition (Primary education)	9361	0.073	0.261	4931	0.069	0.253	4430	0.079	0.269
No school recommendation	9361	0.287	0.452	4931	0.212	0.409	4430	0.370	0.483
Lower school recommendation	9361	0.130	0.336	4931	0.142	0.349	4430	0.116	0.321
Intermediate school recommendation	9361	0.240	0.427	4931	0.272	0.445	4430	0.205	0.404
Upper school recommendation	9361	0.343	0.475	4931	0.375	0.484	4430	0.309	0.462
Grade repetition (Secondary education)	9361	0.143	0.351	4931	0.153	0.360	4430	0.133	0.340
No secondary education enrollment (age 17)	9361	0.031	0.173	4931	0.006	0.080	4430	0.058	0.234
Lower secondary enrollment (age 17)	9361	0.146	0.354	4931	0.158	0.365	4430	0.134	0.341
Intermediate secondary enrollment (age 17)	9361	0.393	0.488	4931	0.409	0.492	4430	0.375	0.484
Upper secondary enrollment (age 17)	9361	0.430	0.495	4931	0.426	0.495	4430	0.433	0.496
Work experience at age 17	9361	0.313	0.464	4931	0.379	0.485	4430	0.241	0.428
Cognitive test available	9361	0.380	0.485	4931	0.382	0.486	4430	0.379	0.485
Cognitive skills	3560	0.000	1.000	1883	0.163	0.973	1677	-0.183	0.998
Diligence skills	9361	-0.000	1.000	4931	-0.085	0.895	4430	0.095	1.098
Social skills	9361	-0.000	1.000	4931	0.011	0.944	4430	-0.013	1.059
Secondary education drop-out	9361	0.155	0.362	4931	0.077	0.266	4430	0.242	0.428
Lower secondary education	9361	0.163	0.369	4931	0.180	0.384	4430	0.144	0.351
Intermediate secondary education	9361	0.406	0.491	4931	0.437	0.496	4430	0.372	0.484
Upper secondary education	9361	0.276	0.447	4931	0.306	0.461	4430	0.242	0.429
Tertiary education enrollment	9361	0.398	0.490	4931	0.500	0.500	4430	0.285	0.451
Tertiary education	9361	0.268	0.443	4931	0.379	0.485	4430	0.144	0.351
Wage (first job) observed	9361	0.602	0.489	4931	0.692	0.462	4430	0.502	0.500
Log hourly wage (first job)	5640	1.647	0.697	3414	1.623	0.664	2226	1.684	0.744
Log net wage (first job)	5665	5.867	0.832	3422	5.870	0.745	2243	5.863	0.949
Log net wage (work year 2)	3255	6.181	0.665	2228	6.127	0.633	1027	6.298	0.716
Log net wage (work year 3)	2639	6.381	0.665	1904	6.338	0.656	735	6.493	0.675
Log net wage (work year 4)	1942	6.651	0.736	1473	6.626	0.727	469	6.727	0.760
Observations	9,361			4,931			4,430		

NOTE.— Observed values denote the count of non-missing observations for each endogenous variable. Cognitive test available is a dummy indicating if the individuals have participated and finalised the cognitive test (Data COGDJ). Log hourly wage is measured in the first observed job; later wages are used only in the present-value robustness check.

Measurement system for skills I construct skill measures by linking the Youth questionnaire (JUGENDL) to the cognitive test module (COGDJ). The COGDJ module contains three standardised tests, covering verbal, numerical, and figural abilities, with 20 items in each domain.³⁸ The Youth questionnaire provides additional measures of school performance, course choices, personality traits, time use, aspirations, preferences, and related non-cognitive measures.³⁹

The baseline measurement system recovers three latent skill dimensions measured at age 17: cognitive skills, (θ^{cog}), social skills, (θ^{soc}), and diligence skills, (θ^{dil}). The cognitive factor is based on standardised test items, school-performance measures, and related schooling information. The two non-cognitive factors are estimated from personality, preference, time-use, extracurricular, aspiration, and behavioural measures. I label these factors social skills and diligence skills based on their loading patterns. The social factor loads strongly on communicative, outgoing, sociable, and interpersonal measures. The diligence factor loads strongly on working carefully, carrying out duties efficiently, not being lazy, patience, and related measures of effort, focus, and conscientious behaviour. These labels are consistent with the broader literature that distinguishes multiple socio-emotional dimensions rather than summarising all non-cognitive traits in a single factor (Deming, 2017; Toppeta, 2022; Humphries et al., 2023). These labels are also consistent with the psychometric distinction between externalizing and internalizing socio-emotional dimensions (Achenbach, 1966; Goodman, 1997, 2001; Goodman et al., 2010; Achenbach et al., 2016; Toppeta, 2022).

Before estimating the confirmatory factor system, I use principal component analysis (PCA) and exploratory factor analysis (EFA) as diagnostic checks on the dimensionality of the non-cognitive item pool. Figure 6 shows a steep initial drop in the PCA scree plot, while the EFA suggests that several dimensions explain meaningful common variation. Table 13 guides the interpretation of the non-cognitive factors. One factor loads most strongly on communicative, outgoing, and other interpersonal measures, motivating the social-skill dimension. Another factor loads most strongly on working carefully, carrying out duties efficiently, not being lazy, and related conscientiousness measures, motivating the diligence-skill dimension. Other exploratory factors capture emotional-state or neuroticism-related measures and music-related extracurricular activities. These items remain part of the broader measurement environment, but I do not carry these additional ex-

³⁸The cognitive test module uses a shortened version of the I-S-T 2000 R, adapted for the GSOEP panel setting.

³⁹For example, it records whether individuals enrolled in advanced or basic courses in German, mathematics, and foreign languages.

ploratory dimensions forward as separate structural skills.

The exploratory and confirmatory measurement systems are closely aligned. Table 19 shows that the confirmatory social factor, (θ^{soc}), is strongly correlated with the EFA factor associated with interpersonal measures, while the confirmatory diligence factor, (θ^{dil}), is strongly correlated with the EFA factor associated with conscientiousness and effort. The PCA components are less directly interpretable because they combine several dimensions, but they display the same broad separation between social and diligence-related measures. Table 19 further shows that the two non-cognitive factors are moderately correlated with each other, at 0.35, while cognitive skills are only weakly correlated with social skills and diligence skills, at 0.05 and 0.13, respectively. These patterns support treating cognitive, social, and diligence skills as distinct dimensions in the sequential model.

The measurement system combines categorical and continuous items. I use the item-level responses directly, rather than first aggregating them into continuous subscales, so that the factor model exploits variation across the full set of observed measures. The non-cognitive factors are estimated from measures of personality, locus of control, preferences, time use, extracurricular activities, aspirations, and related age-17 outcomes; the full list is reported in Table 23.

Cognitive skills are identified from dedicated cognitive and school-performance measures:

$$m_{ij}^c = a_j^c + \lambda_j^c \theta_i^{cog} + \epsilon_{ij}^c. \quad (11)$$

Social and diligence skills are identified jointly from the non-cognitive measurement system, allowing the same observed item to load on both latent dimensions. For the non-cognitive measurement system, I estimate a two-factor model:

$$m_{ij}^{nc} = a_j^{nc} + \lambda_j^d \theta_i^{dil} + \lambda_j^s \theta_i^{soc} + \epsilon_{ij}^{nc}. \quad (12)$$

I label the first non-cognitive factor diligence, θ^{dil} , because it loads on measures related to working carefully, carrying out duties efficiently, not being lazy, patience, and conscientious behaviour. I label the second factor social skills, θ^{soc} , because it loads on measures related to communication, sociability, extraversion, leadership, and interpersonal engagement. These two factors are distinct but not mutually exclusive: individuals may score highly on both dimensions. Table

23 reports the full measurement system for the latent skill factors. The baseline system uses 75 measures for cognitive skills, θ^{cog} , and 76 measures for the two non-cognitive factors, diligence θ^{dil} and social skills θ^{soc} .⁴⁰

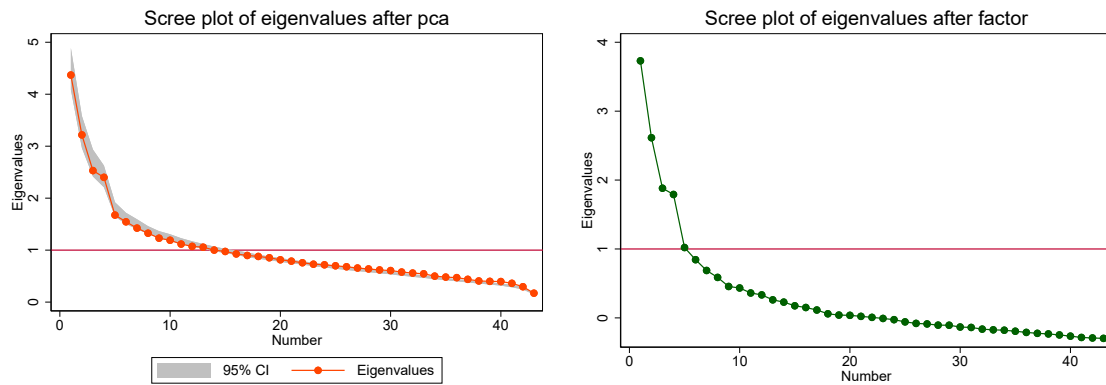
Because some cognitive measures may partly reflect family investments and schooling environments rather than cognitive performance alone, I report robustness checks using alternative cognitive factors. In particular, I construct a test-score-only cognitive factor that excludes school-performance and parental-involvement measures. I also construct a trimmed cognitive factor designed to improve cross-cohort comparability.

For the measurement-robustness specifications, I also construct dedicated social and diligence factors. These factors use the same age-17 non-cognitive item pool but impose a more restrictive measurement system: each observed item is assigned to only one latent dimension. The dedicated social factor is estimated from measures that load strongly on the interpersonal dimension, including being communicative, introducing new ideas, being outgoing or sociable, lively imagination, being relaxed, class-representative participation, and risk tolerance. The dedicated diligence factor is estimated from measures that load strongly on effort and conscientious behaviour, including working carefully, carrying out duties efficiently, being considerate and friendly, future-oriented behaviour, self-confidence, and curiosity. I estimate each dedicated factor as a separate one-factor latent model, orient the scores so that higher values indicate higher skills, and standardise them in the pooled sample before the cohort split.

Appendix Tables 14–16 report measurement-invariance tests for the skill factors. These tests are diagnostic for the cohort-comparability assumption. The baseline cognitive factor does not satisfy exact loading invariance across cohorts. I therefore construct a trimmed cognitive factor using a reduced item set, for which loading invariance is not rejected. For the dedicated social and diligence factors, likelihood-ratio tests reject exact loading invariance, while information criteria provide more mixed evidence and often favour the more restricted specifications. For this reason, I interpret the baseline estimates as comparisons under a pooled normalisation and use the measurement-invariant factors as robustness checks.

⁴⁰Italicised measures are used as reference measures for factor normalisation: mathematics grade for θ^{cog} , working carefully for θ^{dil} , and being communicative for θ^{soc} .

Figure 6: GSOEP PCA and EFA Analysis



NOTE.— The figure reports scree plots from principal-component analysis (left panel) and exploratory factor analysis (right panel) for the age-17 non-cognitive skill measures in the GSOEP youth questionnaire. The horizontal red line marks the eigenvalue-one rule. Both plots show that a small number of latent dimensions explain most of the common variation across the observed measures. The exploratory analysis is used to guide the confirmatory measurement system for non-cognitive skills and to discipline the construction of the dedicated social and diligence factors. The final factor definitions are not based mechanically on the eigenvalue-one rule alone; they also use the rotated loading patterns reported in Table 13 and the economic interpretation of the measures.

Table 13: EFA and Correlation with Measures

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

NOTE.— The table reports rotated exploratory factor loadings for the non-cognitive skill measures observed in the youth questionnaire at age 17. The exploratory factor analysis is used to discipline the construction and interpretation of the latent non-cognitive skill factors. Entries report the association between each observed measure and each extracted factor; blank cells indicate loadings below the reporting threshold. Bold entries mark the main loading used to interpret the factor. Factor 2 loads most strongly on communicative, outgoing, and social-interaction measures and motivates the social-skill dimension. Factor 4 loads most strongly on working carefully, carrying out duties efficiently, not being lazy, self-confidence, and future-oriented behaviour and motivates the diligence-skill dimension. The uniqueness column reports the share of each variable's variance not explained by the extracted factors. The dedicated social and diligence factors used in robustness exercises are constructed by assigning selected high-loading measures to a single latent factor, following the dedicated-measurement-system logic in Attanasio et al. (2020).

Table 14: Measurement-Invariance Tests for the Cognitive Skill Factor (Baseline)

Model	N_p	Log likelihood	AIC	BIC	Comparison	LR statistic	df	p-value	Δ AIC	Δ BIC
Baseline/configural	302	-122830.1	246264.3	248129.9						
Threshold/intercept invariance	228	-123307.8	247071.6	248480.2	vs. baseline	955.40	74	0.000	807.4	350.2
Loading invariance	229	-122895.9	246249.8	247664.5	vs. baseline	131.51	73	0.000	-14.5	-465.5
Loading and threshold/intercept invariance	155	-123441.8	247193.6	248151.1	vs. threshold/intercept	267.90	73	0.000	121.9	-329.1

NOTE.—The table reports likelihood-based measurement-invariance tests for the cognitive skill factor estimated by Stata `gsem`. The baseline model imposes the same one-factor structure across cohorts but allows item parameters to differ by cohort. The threshold/intercept-invariant model imposes equality of item constants across cohorts. For binary probit items, these constants correspond to item thresholds up to sign. The loading-invariant model imposes equality of factor loadings across cohorts and is the key restriction for placing the latent cognitive factor on a common scale. The last row imposes both loading and threshold/intercept restrictions. N_p is the number of estimated parameters. Δ AIC and Δ BIC compare each restricted model to the model named in the comparison column.

Table 15: Measurement-Invariance Tests for the Cognitive Skill Factor (Measurement-invariant)

Model	N_p	Log likelihood	AIC	BIC	Comparison	LR statistic	df	p -value	Δ AIC	Δ BIC
Baseline/configural	238	-104508.7	209493.5	210963.8	—	—	—	—	—	—
Threshold/intercept invariance	180	-104891.3	210142.6	211254.6	vs. baseline	765.13	58	0.000	649.1	290.8
Loading invariance	181	-104536.7	209435.3	210553.5	vs. baseline	55.85	57	0.518	-58.2	-410.3
Loading and threshold/intercept invariance	123	-104970.0	210186.0	210945.9	vs. threshold/intercept	157.43	57	0.000	43.4	-308.7

NOTE.—The table reports likelihood-based measurement-invariance tests for the cognitive skill factor estimated by Stata `gsem`. The baseline model imposes the same one-factor structure across cohorts but allows item parameters to differ by cohort. The threshold/intercept-invariant model imposes equality of item constants across cohorts. For binary probit items, these constants correspond to item thresholds up to sign. The loading-invariant model imposes equality of factor loadings across cohorts and is the key restriction for placing the latent cognitive factor on a common scale. The last row imposes both loading and threshold/intercept restrictions. N_p is the number of estimated parameters. Δ AIC and Δ BIC compare each restricted model to the model named in the comparison column. Standard covariance-structure fit indices such as RMSEA, CFI, TLI, and SRMR are not reported because they are not standard after nonlinear `gsem` models with mixed continuous and probit indicators.

Table 16: Measurement-Invariance Tests for Dedicated Social and Diligence Factors

Factor	Model	N_p	Log likelihood	AIC	BIC	Comparison	LR statistic	df	p -value	Δ AIC	Δ BIC
Social	Baseline/configural	38	-80590.5	161257.0	161521.6	—	—	—	—	—	—
Social	Threshold/intercept invariance	31	-80617.2	161296.5	161512.3	vs. baseline	53.47	7	0.000	39.5	-9.3
Social	Loading invariance	32	-80602.3	161268.7	161491.5	vs. baseline	23.67	6	0.001	11.7	-30.1
Social	Loading and threshold/intercept invariance	25	-80629.5	161309.1	161483.2	vs. threshold/intercept	24.63	6	0.000	12.6	-29.1
Diligence	Baseline/configural	34	-66190.7	132449.4	132686.1	—	—	—	—	—	—
Diligence	Threshold/intercept invariance	28	-66281.3	132618.7	132813.6	vs. baseline	181.29	6	0.000	169.3	127.5
Diligence	Loading invariance	29	-66204.4	132466.9	132668.8	vs. baseline	27.50	5	0.000	17.5	-17.3
Diligence	Loading and threshold/intercept invariance	23	-66295.9	132637.8	132797.9	vs. threshold/intercept	29.14	5	0.000	19.1	-15.7

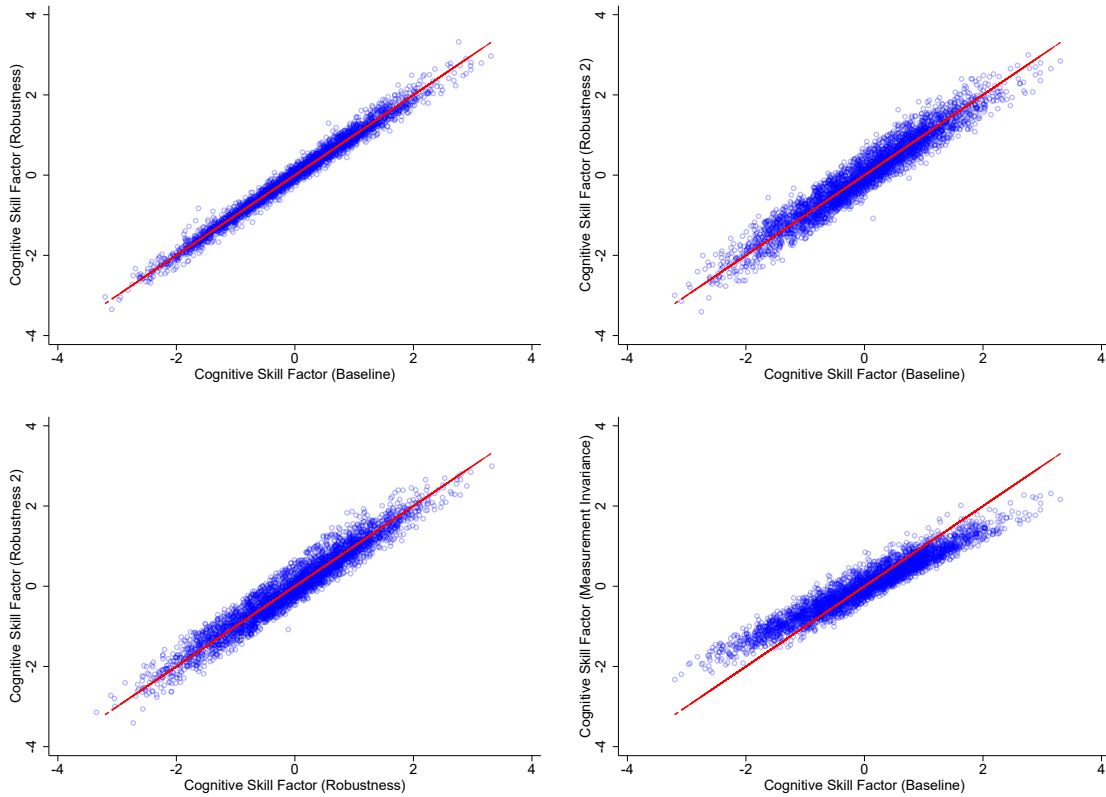
NOTE.—The table reports likelihood-based measurement-invariance tests for dedicated social and diligence factors estimated by Stata `gsem`. The baseline model imposes the same one-factor structure across cohorts but allows item parameters to differ by cohort. The threshold/intercept-invariant model imposes equality of item constants across cohorts. For binary probit items, these constants correspond to item thresholds up to sign. The loading-invariant model imposes equality of factor loadings across cohorts and is the key restriction for placing each latent factor on a common scale. The last row for each factor imposes both loading and threshold/intercept restrictions. N_p is the number of free parameters. Δ AIC and Δ BIC compare each restricted model to the model named in the comparison column.

Table 17: Multidimensional skills by cohort

	Full sample			M (1987-1995)			Z (1996-2003)		
	Observed values	Mean	SD	Observed values	Mean	SD	Observed values	Mean	SD
Cognitive skills (θ^{cog})	3,560	0.000	1.000	1,883	0.163	0.973	1,677	-0.183	0.998
Cognitive skills (θ^{cog} , Robustness I)	3,560	0.000	1.000	1,883	0.177	0.971	1,677	-0.198	0.995
Cognitive skills (θ^{cog} , Robustness II)	3,560	0.000	1.000	1,883	0.001	0.996	1,677	0.000	1.004
Cognitive skills (θ^{cog} , measurement-invariant)	3,560	0.000	0.738	1,883	0.000	0.727	1,677	0.000	0.750
Diligence skills (θ^{dil})	9,361	-0.000	1.000	4,931	-0.085	0.895	4,430	0.095	1.098
Diligence skills (θ^{dil} , dedicated/MI specification)	9,361	-0.000	0.772	4,931	-0.054	0.693	4,430	0.060	0.848
Social skills (θ^{soc})	9,361	-0.000	1.000	4,931	0.011	0.944	4,430	-0.013	1.059
Social skills (θ^{soc} , dedicated/MI specification)	9,361	-0.000	0.796	4,931	0.035	0.650	4,430	-0.040	0.930
Conscientiousness (θ^{cons})	7,023	0.000	1.000	2,627	-0.009	0.986	4,396	0.005	1.008
Extroversion (θ^{extr})	7,023	0.000	1.000	2,627	0.080	0.944	4,396	-0.048	1.029
Self-Esteem	9,361	-0.000	1.000	4,931	-0.156	1.066	4,430	0.174	0.890
Locus of control	9,361	-0.000	1.000	4,931	0.007	0.843	4,430	-0.008	1.150
Observations	9,361			4,931			4,430		

NOTE.— The table reports the distribution of the baseline and alternative skill factors by cohort. The number of observations differs across factors because cognitive skills require completed cognitive-test information and sufficient item coverage in the cognitive measurement system, while non-cognitive skills are measured in the broader Youth questionnaire sample. Cognitive skills (Robust 1) are constructed using only the cognitive test-score items administered in the SOEP, excluding school-performance and parental-involvement measures. Cognitive skills (Robust 2) use the same test-score items as Robust 1, but follow Izadi and Tuhkuri (2026) by standardising the latent factor within each survey year at age 17 and then re-standardising it in the full sample. The dedicated social and diligence factors are constructed from separate high-loading item sets selected from the EFA/CFA evidence, so that each item loads on only one non-cognitive dimension.

Figure 7: Correlation of cognitive skill factors



NOTE.— The figure compares alternative constructions of the cognitive skill factor measured at age 17. Each panel plots individual predicted factor scores from two measurement systems against each other; the dashed red line is the 45-degree line. The upper-left panel compares the baseline cognitive factor, which combines standardised cognitive-test items, grades, advanced-course indicators, school-related measures, and parental-involvement measures, with a robustness factor constructed using only standardised cognitive-test items. The upper-right panel compares the baseline factor with an alternative test-score factor that is estimated separately by survey year and then re-standardised in the pooled sample. The lower-left panel compares the two test-score-only robustness measures. The lower-right panel compares the baseline factor with the measurement-invariance cognitive factor constructed from the trimmed item set used in the cohort-invariance test. All factors are oriented so that higher values correspond to higher cognitive skills.

Table 18: Interpretation of Latent Factors

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

NOTE.—The table reports pairwise correlations between the standardized latent factors used in the main analysis and SOEP Big Five personality items. θ^{cog} denotes the cognitive skill factor, θ^{dil} the diligence factor, and θ^{soc} the social skill factor. Big Five items are coded so that higher values indicate stronger agreement with the statement. Positive entries indicate that individuals with higher values of the latent factor tend to score higher on the item, while negative entries indicate the opposite. Bold entries highlight the correlations most informative for interpreting the diligence and social skill factors.

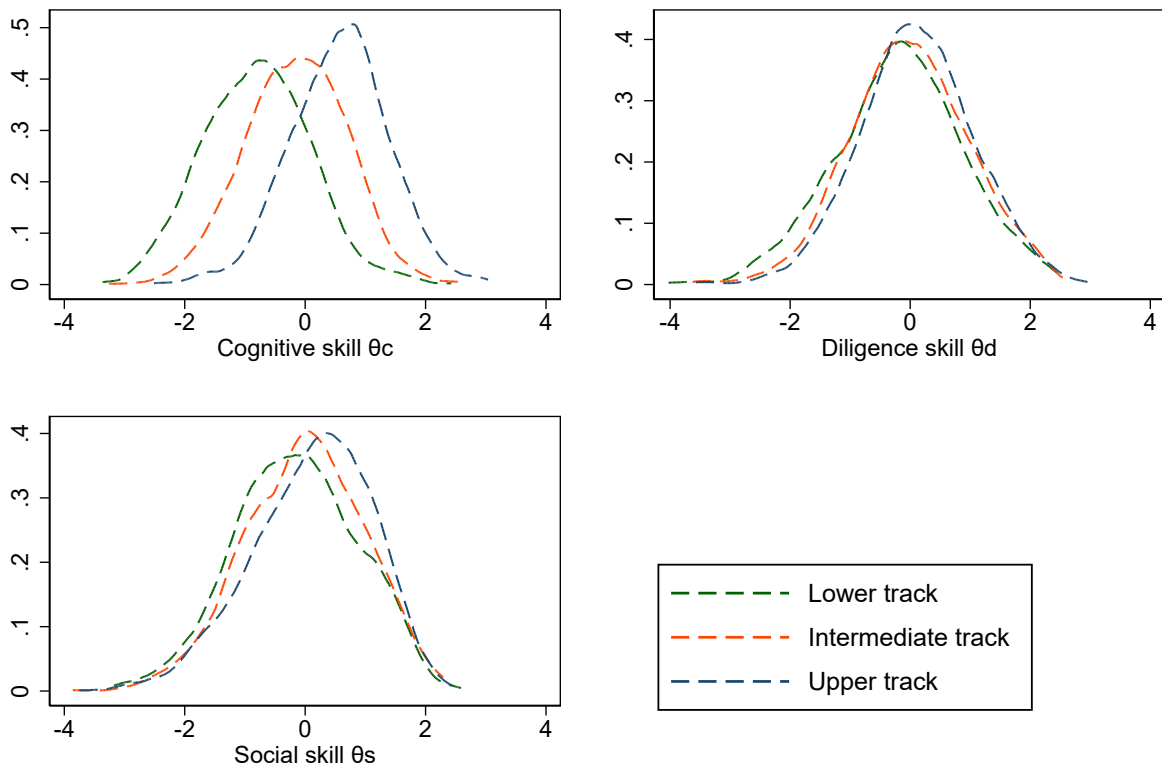
Table 19: Correlations across skill measurement systems

Validation exercise	Measure	Cognitive skills θ^{cog}	Diligence skills θ^{dil}	Social skills θ^{soc}
<i>Panel A. Principal-component diagnostics</i>				
PCA	Component 1	–	0.689	0.876
PCA	Component 2	–	0.245	0.002
PCA	Component 3	–	-0.535	0.446
PCA	Component 4	–	0.377	-0.058
<i>Panel B. Exploratory-factor diagnostics</i>				
EFA	Factor 1	–	0.037	0.921
EFA	Factor 2	–	0.958	0.305
EFA	Factor 3	–	-0.208	-0.241
EFA	Factor 4	–	0.183	0.210
<i>Panel C. Robustness and alternative measurement systems</i>				
Alternative factor	Robustness I	0.992	–	–
Alternative factor	Robustness II	0.963	–	–
Alternative factor	Measurement-invariant	0.960	–	–
Alternative factor	Dedicated / MI specification	–	0.921	0.853
<i>Panel D. Correlations among baseline structural skill factors</i>				
Baseline factor	Cognitive skills θ^{cog}	1.000	0.131	0.090
Baseline factor	Diligence skills θ^{dil}	0.131	1.000	0.358
Baseline factor	Social skills θ^{soc}	0.090	0.358	1.000

NOTE.—Panels A and B compare the baseline non-cognitive skill factors with principal components and exploratory factors from the exploratory measurement system. Bold entries indicate the largest absolute correlation within the PCA or EFA block for each non-cognitive factor. Panel C reports correlations between each baseline factor and the corresponding robustness, dedicated, or measurement-invariant measure. Panel D reports correlations among the three baseline structural skill factors. PCA and EFA signs are arbitrary; correlations should therefore be interpreted up to factor orientation.

Figure 8: Distribution of skills across high-school tracks

Distribution of Skills Across High School Tracks



NOTE.— The figure plots kernel density estimates of the three latent skill factors measured at age 17, separately by secondary school track. Lower, intermediate, and upper tracks refer to the realised secondary school track attended by the individual. Cognitive skills are denoted by θ^{cog} , diligence skills by θ^{dil} , and social skills by θ^{soc} . All factors are standardised in the pooled sample to have mean zero and standard deviation one, with higher values indicating higher skills. The figure shows strong sorting by cognitive skills across tracks, while the distributions of diligence and social skills overlap more substantially. Details on the construction of the latent factors are provided in Appendix A.1: GSOEP.

A.2: ESCO The ESCO dictionary reports occupation-level skill requirements, which I use to proxy occupational task content. It contains information on 13,890 task descriptions for 3,008 occupations (ISCO-08). These task descriptions are further grouped by ESCO in broader skill categories. I further reduce the dimensionality of this dataset by extracting three main factors. These are measures of task content, following closely Deming (2017): routine, non-routine analytical (cognitive), and social tasks.

I first aggregate the 13,890 detailed ESCO skill requirements into 101 broader skill groups, including transversal skills and competences.⁴¹ I then construct occupation-by-skill-group indicators. For each ISCO-08 occupation and each broad skill group, the indicator equals one if ESCO lists at least one detailed skill requirement from that group as essential or optional for the occupation, and zero otherwise. This produces a high-dimensional occupation-level measurement system, which I then reduce to a smaller set of task-content factors.

Then, I link the resulting task content classification to the GSOEP, which includes detailed individual-level labour market histories from 1984 to 2020 in Germany, using ISCO-08 codes.⁴² I perform various robustness checks using alternative measures from ESCO and O*NET.

Measurement system for tasks I reduce the high-dimensional ESCO measurement system to a small set of task-content measures for German occupations. As a first exploratory step, I perform principal-component analysis using 101 broad ESCO skill groups. Figure 9 shows a steep initial decline, suggesting a low-dimensional structure. Guided by the established task-based literature and interpretability, I focus on a three-factor structure, representing social, routine, and non-routine analytical tasks, which I then validate using exploratory and confirmatory factor analysis (Deming, 2017).

I then use exploratory factor analysis (EFA) to check whether the same structure appears when common factors, rather than principal components, are extracted. The EFA results also support a three-factor structure. Table 20 shows that the first three PCA components are strongly correlated

⁴¹The complete list of broader ESCO skill groups is available at ESCO skill groups.

⁴²Table 21 in Appendix includes a set of the top 10 ISCO-08 occupations sorted based on task content. For instance, occupations intensive in social tasks are, among others: 'Policy administration professionals', 'Sports, recreation and cultural centre managers' and 'Advertising and marketing professionals'. Occupations with a high content of routine tasks are, for instance: "Metal working machine tool setters and operators" or "Mechanical engineering technicians". Last, occupations with high cognitive task content are: "University and higher education teachers", "Industrial and production engineers" and "Electronics engineers".

with the first three EFA factors.

I use confirmatory factor analysis (CFA) to map ESCO skill requirements into three occupation-level task-content measures: routine, non-routine analytical, and social tasks. This mapping follows the task-based literature, where observed occupational requirements are interpreted as indicators of the tasks performed in an occupation (Deming, 2017). The CFA allows the ESCO indicators to load on latent task dimensions while accounting for measurement error. For identification, I assign dedicated reference measures to each factor and normalise the corresponding loading to one. Table 25 reports the measurement system, including both ESCO skill groups and transversal skills and competences.

For each occupation i and broad ESCO skill group j , I define $m_{ij}^E = 1$ if ESCO lists at least one detailed skill requirement from group j as essential or optional for occupation i , and $m_{ij}^E = 0$ otherwise. I model these indicators as measurements of three latent task-content dimensions, $\Gamma_i = (\gamma_i^S, \gamma_i^R, \gamma_i^C)$, corresponding to social, routine, and non-routine analytical tasks:

$$\Pr(m_{ij}^E = 1 \mid \Gamma_i) = F \left(a_j + \lambda_j^S \gamma_i^S + \lambda_j^R \gamma_i^R + \lambda_j^C \gamma_i^C \right), \quad (13)$$

where $F(\cdot)$ denotes the link function used for the binary measurement model. The loadings λ_j^S , λ_j^R , and λ_j^C are item-specific factor loadings. The resulting factors are interpreted as occupation-level measures of social, routine, and non-routine analytical task content.

Table 20 compares the task measures obtained from PCA, EFA, and CFA. The social-task factor is strongly correlated with the first PCA component and the first EFA factor, while the routine-task factor is strongly correlated with the second PCA component and the second EFA factor. The non-routine analytical factor is also related to the first PCA component and the first EFA factor, reflecting the well-documented overlap between analytical and social task content (Deming, 2017). Overall, the exploratory and confirmatory measurement systems yield similar task dimensions.

Table 20 compares the ESCO-based task measures with corresponding O*NET measures. The correlations are positive along the expected dimensions: the ESCO social factor is most strongly correlated with O*NET social tasks, the ESCO routine factor with O*NET routine tasks, and the ESCO cognitive factor with O*NET math tasks. This supports the interpretation of the ESCO factors as measures of occupation-level task content. At the same time, ESCO is based on ISCO-08

occupations and provides more detailed occupational variation than the OCC1990-based measures commonly used with O*NET (Deming, 2017).

As a robustness check, I construct continuous task-content measures that do not rely on latent factors. For each occupation, these measures count the number of ESCO skill requirements belonging to selected broad groups associated with social, routine, and non-routine analytical tasks. Table 22 reports the broad groups used to construct these measures, and Table 20 shows that the resulting continuous measures are strongly correlated with the corresponding factor-based measures.

Figure 9: ESCO PCA and EFA Analysis

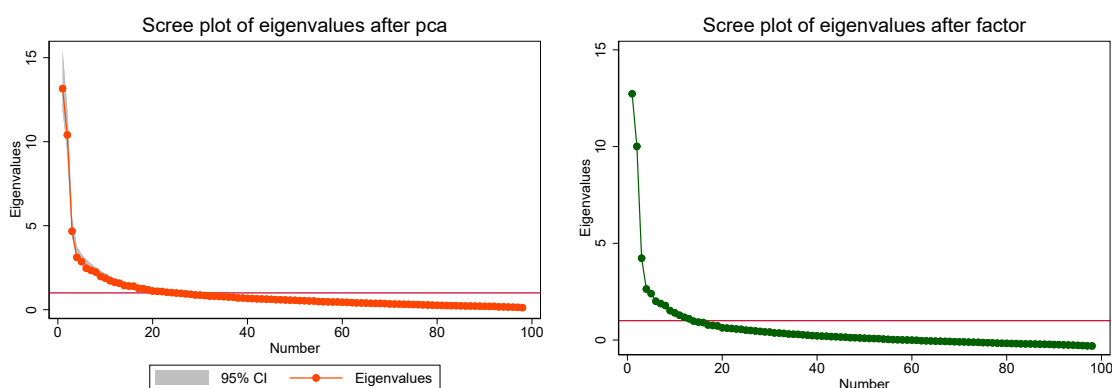


Table 20: Correlations between ESCO task factors and alternative task measures

Validation exercise	Measure	Social task content γ^S	Routine task content γ^R	Cognitive task content γ^C
<i>Panel A. Principal-component diagnostics from ESCO skill requirements</i>				
PCA	Component 1	0.960	-0.010	0.793
PCA	Component 2	-0.026	0.957	0.377
PCA	Component 3	0.282	-0.116	-0.339
<i>Panel B. Exploratory-factor diagnostics from ESCO skill requirements</i>				
EFA	Factor 1	0.713	0.149	0.915
EFA	Factor 2	-0.036	0.926	0.296
EFA	Factor 3	0.730	-0.187	0.088
<i>Panel C. Continuous ESCO robustness measures</i>				
Continuous ESCO measure	Social task content	0.971	-0.032	0.677
Continuous ESCO measure	Routine task content	-0.042	0.912	0.271
Continuous ESCO measure	Cognitive task content	0.818	0.226	0.885
<i>Panel D. O*NET task measures</i>				
O*NET measure	Social task content	0.558	-0.410	0.271
O*NET measure	Routine task content	-0.436	0.404	-0.014
O*NET measure	Math / non-routine analytical	0.393	-0.170	0.467
<i>Panel E. Correlations among final ESCO task factors</i>				
Final ESCO factor	Social task content γ^S	1.000	-0.020	0.686
Final ESCO factor	Routine task content γ^R	-0.020	1.000	0.501
Final ESCO factor	Cognitive task content γ^C	0.686	0.501	1.000

NOTE.—Entries are correlations at the ISCO-08 occupation level. Panels A and B compare the final ESCO task factors with principal components and exploratory factors from the ESCO skill-requirement measurement system. Bold entries in Panels A and B indicate the largest absolute correlation within the PCA or EFA block for each final ESCO factor. Panel C compares the final ESCO factors with continuous ESCO task measures constructed from skill groups. Panel D compares the final ESCO factors with O*NET task measures. Bold entries in Panels C and D indicate the conceptually corresponding task dimension. Panel E reports correlations among the final ESCO task factors. PCA and EFA signs are arbitrary; correlations should therefore be interpreted up to factor orientation.

Table 21: Top 10 ISCO-08 Occupations by Factor of Task Content

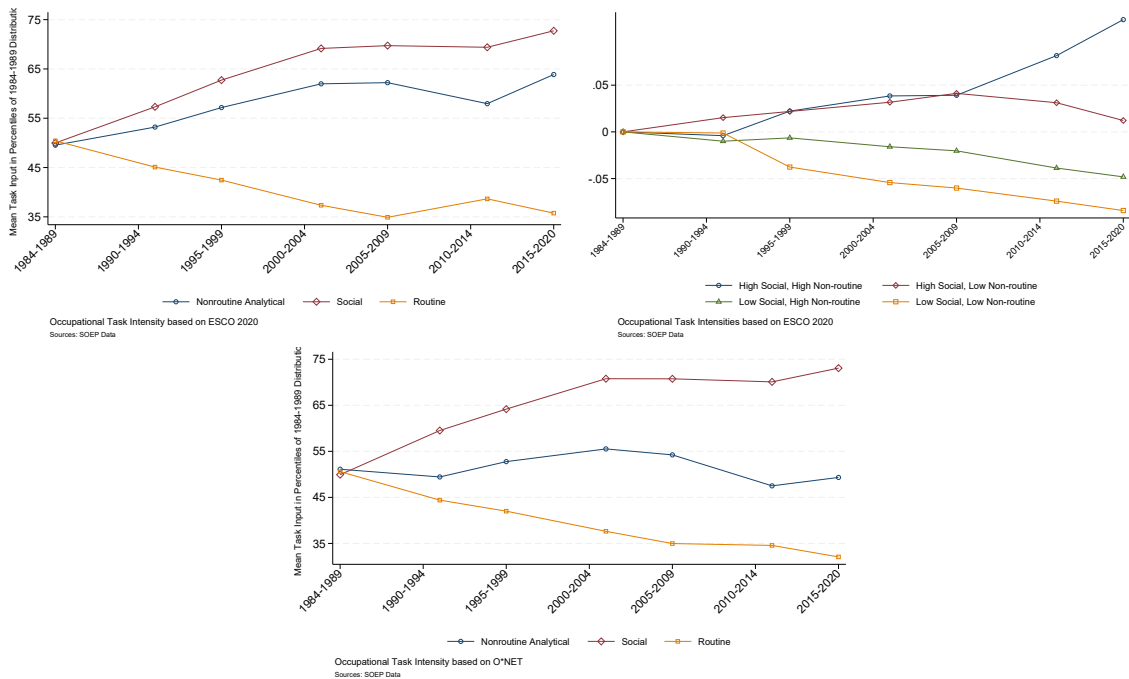
Social	Routine	Cognitive
1349-Professional services managers not elsewhere classified	3115-Mechanical engineering technicians	2149-Engineering professionals not elsewhere classified
2310-University and higher education teachers	3119-Physical and engineering science technicians not elsewhere classified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

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

Table 22: Broader groups and task content

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

Figure 10: Robustness check: continuous measures and O*NET



NOTE.— The figure reports robustness checks using alternative occupation-level task measures. The first two panels use continuous ESCO task measures, constructed from the number of ESCO skill requirements in social, routine, and non-routine analytical task groups. The third panel uses the corresponding O*NET task measures from Deming (2017). The sample is employed GSOEP respondents observed between 1984 and 2020, grouped into five-year periods. Task inputs are weighted by hours worked. Mean task inputs are reported as percentiles of the 1984–1989 distribution. Employment-share changes are measured relative to 1984–1989 for occupations classified in the initial period by whether social and non-routine analytical task intensity are above or below the median.

Measurement systems

Table 23: Measurement system for latent factors θ^{cog} , θ^{dil} and θ^{soc} (GSOEP)

Measures		θ^c	θ^d	θ^s
Data on cognitive tests (COGDJ)				
20 Analogies questions	<i>b</i>	x		
20 Arithmetic Operator questions	<i>b</i>	x		
20 Figures questions	<i>b</i>	x		
Youth Questionnaire (JUGENDL)				
Grade German	<i>c</i>	x		
<i>Grade Mathematics</i>	<i>c</i>	x		
Grade 1. Foreign Language	<i>c</i>	x		
Advanced Course German	<i>b</i>	x		
Advanced Course Mathematics	<i>b</i>	x		
Advanced Course 1. Foreign Language	<i>b</i>	x		
Support tutor	<i>b</i>	x		
Abitur preferred certificate	<i>b</i>	x		
Parents Show Interest In Performance	<i>b</i>	x		
Parents Help With Studying	<i>b</i>	x		
Disagreements With Parents Over Studies	<i>b</i>	x		
Parents Take Part In Parents-Evening	<i>b</i>	x		
Parents Come To Teacher Office Hours	<i>b</i>	x		
Parents Visit Teacher Outside Office Hrs.	<i>b</i>	x		
Involved As Parents Representative	<i>b</i>	x		
Class Representative	<i>b</i>		x	x
Student Body President	<i>b</i>		x	x
Involved With School Newspaper	<i>b</i>		x	x
Belong To Theatre, Dance Group	<i>b</i>		x	x
Belong To Choir, Orchestra, Music Group	<i>b</i>		x	x
Belong To Volunteer Sport Group	<i>b</i>		x	x
Other Kind Of School Group	<i>b</i>		x	x
Musical Lessons Outside Of School	<i>b</i>		x	x
Musically Active	<i>b</i>		x	x
Sport Activity	<i>b</i>		x	x
Take Part In Competitions In This Sport	<i>b</i>		x	x
How Often Listen To Music	<i>c</i>		x	x
How Often Play Music Or Sing	<i>c</i>		x	x
How Often Do Sports	<i>c</i>		x	x
How Often Dance Or Act	<i>c</i>		x	x
How Often Do Tech. Activities	<i>c</i>		x	x
How Often Read	<i>c</i>		x	x
How Often Spend Time Steady Boy-,Girlfriend	<i>c</i>		x	x
How Often Spend Time Best Friend	<i>c</i>		x	x
How Often Spend Time Clique	<i>c</i>		x	x
How Often Youth Centre, Community Centre	<i>c</i>		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 Language	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
<i>Personal characteristics: work carefully</i>	c	X	
<i>Personal characteristics: communicative</i>	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: carry out 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	<i>c</i>	X	X
What a person achieves in life is above all a question of fate or luck	<i>c</i>	X	X
I frequently have the experience that other people have a controlling influence over my life	<i>c</i>	X	X
You have to work hard to succeed	<i>c</i>	X	X
When I run up against difficulties in life, I often doubt my own abilities	<i>c</i>	X	X
The opportunities that I have in life are determined by social conditions	<i>c</i>	X	X
Innate abilities are more important than any efforts one can make	<i>c</i>	X	X
I have little control over the things that happen in my life	<i>c</i>	X	X
If a person is socially or politically active, he/she can have an effect on social conditions	<i>c</i>	X	X
Amount of close friends	<i>c</i>	X	X

Table 24: Latent factors θ^{cog} , θ^{dil} and θ^{soc} and Correlation with Measures

	θ^{cog}	θ^{dil}	θ^{soc}
Grade German	0.137	0.214	0.065
Grade Foreign Languages	0.177	0.184	0.131
Grade Mathematics	0.221	0.272	0.113
Parents Show Interest In Performance	0.118	-0.176	-0.148
Basic,Advanced Course German	-0.055	0.079	0.142
Basic,Advanced Course Mathematics	0.006	0.13	0.142
Basic,Advanced Course 1. Foreign Language	0.006	0.13	0.142
Paid Tutor	0.008	-0.029	0.039
Parents Help With Studying	0.023	0.006	0.025
Disagreements With Parents Over Studies	-0.135	-0.226	-0.147
Parents Take Part In Parents-Evening	0.111	0.115	0.06
Parents Come To Teacher Office Hours	0.063	0.102	0.191
Parents Visit Teacher Outside Office Hrs.	-0.146	-0.148	-0.043
Involved As Parents Representative	0.218	0.087	-0.02
Analogy task 1	0.292	-0.138	-0.024
Analogy task 2	0.181	0.114	-0.024
Analogy task 3	0.501	-0.01	-0.069
Analogy task 4	0.401	0.056	0.076
Analogy task 5	0.324	0.025	-0.067
Analogy task 6	0.338	0.041	-0.008
Analogy task 7	0.453	0.03	-0.104
Analogy task 8	0.244	0.034	0.009
Analogy task 9	0.405	-0.053	-0.112
Analogy task 10	0.346	0.069	0.007
Analogy task 11	0.352	0.036	-0.013
Analogy task 12	0.224	0.089	-0.018
Analogy task 13	0.201	-0.052	-0.046
Analogy task 14	0.077	0.023	-0.011
Analogy task 15	0.438	0.087	-0.002
Analogy task 16	0.118	0.017	-0.089
Analogy task 17	0.018	0	0.022
Analogy task 18	0.073	0.056	-0.037
Analogy task 19	0.24	0.089	0.134
Analogy task 20	0.162	0.049	-0.039
Task Arithmetic Operator 1	0.265	-0.096	-0.134
Task Arithmetic Operator 2	0.228	-0.02	-0.047
Task Arithmetic Operator 3	0.419	-0.111	-0.168
Task Arithmetic Operator 4	0.577	0.022	-0.015
Task Arithmetic Operator 5	0.577	-0.003	-0.091
Task Arithmetic Operator 6	0.503	0.078	-0.008
Task Arithmetic Operator 7	0.675	0.043	-0.108
Task Arithmetic Operator 8	0.51	-0.025	-0.085
Task Arithmetic Operator 9	0.463	0.061	-0.011
Task Arithmetic Operator 10	0.533	0.019	-0.019
Task Arithmetic Operator 11	0.554	0.029	-0.056
Task Arithmetic Operator 12	0.473	0.064	-0.078

Task Arithmetic Operator 13	0.544	0.085	0.016
Task Arithmetic Operator 14	0.541	-0.009	-0.175
Task Arithmetic Operator 15	0.57	0.099	-0.118
Task Arithmetic Operator 16	0.473	-0.099	-0.107
Task Arithmetic Operator 17	0.611	-0.033	-0.191
Task Arithmetic Operator 18	0.493	0.022	-0.107
Task Arithmetic Operator 19	0.468	0.069	0.03
Task Arithmetic Operator 20	0.407	0.081	0.044
Task Figures 1	0.25	-0.061	-0.116
Task Figures 2	0.243	-0.06	0.084
Task Figures 3	0.325	-0.074	-0.05
Task Figures 4	0.311	-0.053	-0.004
Task Figures 5	0.418	0.062	-0.058
Task Figures 6	0.339	0.008	-0.079
Task Figures 7	0.232	0.073	0.035
Task Figures 8	0.371	-0.037	-0.07
Task Figures 9	0.428	0.003	-0.02
Task Figures 10	0.267	-0.074	-0.082
Task Figures 11	0.262	0.09	0.244
Task Figures 12	0.247	0.055	0.079
Task Figures 13	0.206	0.078	-0.015
Task Figures 14	0.308	0.019	-0.125
Task Figures 15	0.309	0.114	-0.023
Task Figures 16	0.137	0.032	-0.029
Task Figures 17	0.281	0.015	0.01
Task Figures 18	0.096	-0.019	0.008
Task Figures 19	0.145	0.103	-0.202
Task Figures 20	0.042	0.123	-0.105
Self-confidence Factor	-0.123	0.379	0.338
Locus of Control Factor	0.119	0.333	0.095
Personal characteristics: work carefully	-0.053	0.76	0.211
Personal characteristics: communicative	-0.164	0.186	0.84
Personal characteristics: abrasive towards others	-0.084	-0.153	0.277
Personal characteristics: introduce new ideas	-0.092	0.261	0.539
Personal characteristics: often worry	-0.24	-0.104	0.11
Personal characteristics: can forgive others	-0.065	0.271	0.185
Personal characteristics: am lazy	0.107	-0.552	-0.096
Personal characteristics: am outgoing/sociable	-0.137	0.063	0.838
Personal characteristics: importance of esthetics	-0.055	0.247	0.327
Personal characteristics: am nervous	-0.122	-0.051	-0.22
Personal characteristics: carryout duties efficiently	0.048	0.775	0.248
Personal characteristics: reserved	0.061	-0.089	-0.538
Personal characteristics: considerate, friendly	-0.098	0.489	0.252
Personal characteristics: lively imagination	-0.044	0.174	0.391
Personal characteristics: be relaxed, no stress	0.1	0.325	0.391
Personal characteristics: hunger for knowledge, curious	0.172	0.441	0.4
Frequency of Being Angry in the Last 4 Weeks	-0.087	-0.237	-0.001
Frequency of Being Worried in the Last 4 Weeks	-0.087	-0.175	-0.14
Frequency of Being Happy in the Last 4 Weeks	0.044	0.318	0.421
Frequency of Being Sad in the Last 4 Weeks	-0.117	-0.218	-0.196

Class Representative	-0.045	0.247	0.351
Student Body President	-0.017	0.148	0.191
Involved With School Newspaper	0.034	0.165	0.135
Belong To Theatre, Dance Group	0.086	-0.032	0.102
Belong To Choir, Orchestra, Music Group	0.178	0.05	0.019
Belong To Volunteer Sport Group	0.032	-0.087	0.148
Other Kind Of School Group	0.002	0.138	0.078
Musical Lessons Outside Of School	0.296	0.159	0.033
Musically Active	0.283	0.186	0.114
Playing sports	0.048	0.063	0.141
Take Part In Competitions In This Sport	0.128	-0.043	0.056
Personal risk tolerance	-0.162	0.081	0.405
Opinion: Trust People	0.149	0.323	0.103
No more reliance on anyone	-0.065	-0.19	-0.011
Opinion: Distrust Strangers	-0.331	-0.095	0.21
Fun today, don't think about tomorrow	-0.073	-0.402	0.072
Renounce today, afford tomorrow	-0.09	0.257	-0.039
Political Interests	-0.137	-0.279	-0.071
Amount Of Closed Friends	0.173	0.145	0.156
How Often Spend Time Steady Boy-,Girlfriend	-0.046	0.093	0.303
How Often Spend Time Best Friend	-0.033	0.189	0.235

Table 25: Measurement system for latent factors γ^S , γ^R and γ^C (ESCO)

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

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

B: Model

B.1: Bias in direct and total returns Together, these two issues prevent reduced-form regressions from separately identifying direct and total returns to skills. To formalise this bias, consider two skill vectors, Θ and Θ' , holding $X_i = x$ and $\eta_i = m$.⁴³ As in Heckman et al. (2018a), I further assume that, conditional on X_i and η_i , the remaining variation in skills and higher education is not confounded by unobservables.

The bias in Equation (2), corresponding to column (3) of Table 3, arising from not accounting for η_i within education state u , is given by:

$$\begin{aligned}
 & \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u] \end{array} \right]}_{\text{observed wage gap within education state } u} - \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u, \eta_i = m] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u, \eta_i = m] \end{array} \right]}_{\text{direct return within } u \text{ and fixed } \eta_i = m} \\
 &= \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u, \eta_i = m] \end{array} \right]}_{\text{selection on } \eta_i \text{ among } i \text{ with } \Theta_i = \Theta'} - \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u, \eta_i = m] \end{array} \right]}_{\text{selection on } \eta_i \text{ among } i \text{ with } \Theta_i = \Theta}. \quad (14)
 \end{aligned}$$

This bias arises because conditioning on $U_i = u$ does not hold unobserved ability fixed. Moreover, the total observed return to skills does not condition on U_i . It therefore further combines direct returns to skills, indirect effects through higher education completion, and selection on unobserved

⁴³For the purpose of this decomposition, I treat Θ_i as observed. In the empirical model, Θ_i is recovered from the measurement system described in Section 2.2.

endowments. The bias in total returns, column (1) of Table 3, can be decomposed as:

$$\begin{aligned}
& \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta'] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta] \end{array} \right]}_{\text{observed wage gap}} - \underbrace{\left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', \eta_i = m] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, \eta_i = m] \end{array} \right]}_{\text{total return to skills fixed } \eta_i = m} \\
& = \sum_{u=0}^1 \Pr(U_i = u | X_i = x, \Theta_i = \Theta') \underbrace{\left(\begin{array}{c} \left[\mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u] - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u] \right] \\ - \left[\mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u, \eta_i = m] \right. \\ \left. - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u, \eta_i = m] \right] \end{array} \right)}_{\text{selection on } \eta_i \text{ in direct returns within } u} \\
& + \sum_{u=0}^1 \underbrace{\left[\begin{array}{c} \Pr(U_i = u | X_i = x, \Theta_i = \Theta') \\ - \Pr(U_i = u | X_i = x, \Theta_i = \Theta', \eta_i = m) \end{array} \right]}_{\text{selection on } \eta_i \text{ in higher education among } i \text{ with } \Theta_i = \Theta'} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta', U_i = u, \eta_i = m] \\
& - \sum_{u=0}^1 \underbrace{\left[\begin{array}{c} \Pr(U_i = u | X_i = x, \Theta_i = \Theta) \\ - \Pr(U_i = u | X_i = x, \Theta_i = \Theta, \eta_i = m) \end{array} \right]}_{\text{selection on } \eta_i \text{ in higher education among } i \text{ with } \Theta_i = \Theta} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u, \eta_i = m] \\
& + \sum_{u=0}^1 \underbrace{\left[\begin{array}{c} \Pr(U_i = u | X_i = x, \Theta_i = \Theta') \\ - \Pr(U_i = u | X_i = x, \Theta_i = \Theta) \end{array} \right]}_{\text{interaction between induced education sorting and selection on } \eta_i \text{ within education states}} \left[\begin{array}{c} \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u] \\ - \mathbb{E}[Y_i | X_i = x, \Theta_i = \Theta, U_i = u, \eta_i = m] \end{array} \right]. \tag{15}
\end{aligned}$$

The first term is the direct return bias in Equation 14, averaged across higher education using the higher education probability of individuals with $\Theta_i = \Theta'$. The second, third and fourth terms capture selection in higher education probabilities: observed completion probabilities differ from those obtained at fixed $\eta_i = m$ for individuals with $\Theta_i = \Theta'$ and $\Theta_i = \Theta$. In line with Heckman et al. (2018a) and Humphries et al. (2023), the total return to skills combines a direct wage component with continuation-value components operating through later educational choices.⁴⁴

Moreover, the same objects can be indexed by cohort c . I return in Section 4 to the additional assumptions required to compare these returns across cohorts, including the common measurement of multidimensional skills and the proper treatment of cohort-specific unobserved heterogeneity.

⁴⁴Skills measured at age 17 may affect starting wages directly, but they may also affect the probability of completing higher education, thereby opening or closing later wage-relevant states. The coefficient on skills without education controls mixes these components with selection on unobserved endowments. The coefficient controlling for education removes part of the continuation-value channel, but it does not eliminate selection within education states.

B.2: Full model specification

$$\begin{aligned}
\theta^j &= \alpha_0^j + \alpha^{j,X} X + \alpha^{j,\text{Unem}} \text{Unem}^j + \sum_{m=2}^M \mathbf{1}\{\eta_i = m\} \alpha^{j,m} \\
&+ \alpha^{j,\text{delay}^{pe}} \text{delay}^{pe} + \alpha^{j,\text{delay}^{se}} \text{delay}^{se} \\
&+ \alpha^{j,\text{hs_track}_e^{hs}} \text{hs_track}_e^{hs} \\
&+ \alpha^{j,X \times \text{delay}^{pe}} X \cdot \text{delay}^{pe} + \alpha^{j,X \times \text{delay}^{se}} X \cdot \text{delay}^{se} \\
&+ \alpha^{j,X \times \text{hs_track}_e^{hs}} X \cdot \text{hs_track}_e^{hs} + \alpha^{j,\text{WE}} \text{Work_Exp for } j \in \{\text{cog}, \text{dil}, \text{soc}\},
\end{aligned}$$

$$\begin{aligned}
\phi^e(X, \eta, \theta^j, D^e, Z^e) &= \alpha_0^e \cdot \mathbf{1}_{\{e \in \{11, 12\}\}} + \alpha^{e,X} X + \alpha^{e,\text{Unem}} \text{Unem}^e + \sum_{m=2}^M \mathbf{1}\{\eta_i = m\} \alpha^{e,m} \\
&+ \alpha^{e,\text{delay}^{se}} \text{delay}^{se} \\
&+ \alpha^{e,\theta^j} \theta^j + \theta^{\text{cog}} (\alpha^{e,\theta^{\text{cog}} \times \theta^{\text{soc}}} \theta^{\text{soc}} + \alpha^{e,\theta^{\text{cog}} \times \theta^{\text{dil}}} \theta^{\text{dil}}) \\
&+ \alpha^{e,\text{hs_track}^{hs}} \text{hs_track}^{hs} \cdot \mathbf{1}_{\{e \in \{10, 11\}\}} \\
&+ \alpha^{e,\text{WE}} \text{Work_Exp for } e \in E = \{10, 11, 12\},
\end{aligned}$$

B.3: Expectation-maximisation (EM) algorithm I estimate the model using an Expectation-maximisation (EM) algorithm (Arcidiacono and Jones, 2003). This method was originally developed by Dempster et al. (1977), and applied to dynamic discrete choice models by, amongst others, Arcidiacono (2004), Arcidiacono and Miller (2011), and Arcidiacono and Ellickson (2011). This method is composed of (i) an expectation and (ii) a maximisation step. These two steps are repeated until convergence is achieved.

After the maximisation step, we update the conditional probabilities and iterate to the next maximisation. This process is repeated until convergence is obtained. To assess the sensitivity of the model to the number of heterogeneity types, I re-estimate the model by gradually adding types. Since the model may have local optima, I estimate each specification from multiple starting values and compare fit and convergence across specifications.

Appendix Table 26 reports selection statistics across alternative numbers of latent types and random starting values. Although AIC and BIC favour the three-type specification within each

cohort, I use $M = 2$ in the baseline for three reasons. First, the two-type likelihood is essentially invariant to starting values, whereas the three-type estimations converge to distinct local optima across seeds. Second, the central objects of the paper are cross-cohort comparisons of returns. Because latent types are cohort-specific and label-dependent, the comparison requires a type structure that is stable and similarly composed in both cohorts. I therefore treat $M = 3$ as a robustness check: the main conclusions are unchanged, with a larger decline in returns to diligence and a smaller but still significant increase in direct returns to social skills.

Table 26: Model selection for the benchmark specification

Cohort	Types	Seed	Selected	N	N_p	Neg. log likelihood	AIC	BIC	Role
M (1987-1995)	2	1		4931	383	37810.367	76386.7	78877.5	Baseline
M (1987-1995)	2	2		4931	383	37810.182	76386.4	78877.1	Baseline
M (1987-1995)	2	3	Yes	4931	383	37810.170	76386.3	78877.1	Baseline
M (1987-1995)	2	4		4931	383	37810.305	76386.6	78877.4	Baseline
M (1987-1995)	2	5		4931	383	37810.271	76386.5	78877.3	Baseline
M (1987-1995)	3	1		4931	401	36741.384	74284.8	76892.6	Robustness
M (1987-1995)	3	2		4931	401	36847.524	74497.0	77104.9	Robustness
M (1987-1995)	3	3	Yes	4931	401	36738.572	74279.1	76887.0	Robustness
M (1987-1995)	3	4		4931	401	36859.777	74521.6	77129.4	Robustness
M (1987-1995)	3	5		4931	401	36741.008	74284.0	76891.8	Robustness
Z (1996-2003)	2	1	Yes	4430	383	34304.119	69374.2	71824.0	Baseline
Z (1996-2003)	2	2		4430	383	34304.167	69374.3	71824.1	Baseline
Z (1996-2003)	2	3		4430	383	34304.150	69374.3	71824.0	Baseline
Z (1996-2003)	2	4		4430	383	34304.192	69374.4	71824.1	Baseline
Z (1996-2003)	2	5		4430	383	34304.198	69374.4	71824.1	Baseline
Z (1996-2003)	3	1		4430	401	33272.440	67346.9	69911.7	Robustness
Z (1996-2003)	3	2		4430	401	33272.255	67346.5	69911.4	Robustness
Z (1996-2003)	3	3		4430	401	33272.346	67346.7	69911.6	Robustness
Z (1996-2003)	3	4		4430	401	33272.298	67346.6	69911.5	Robustness
Z (1996-2003)	3	5		4430	401	33288.385	67378.8	69943.6	Robustness
Z (1996-2003)	3	6	Yes	4430	401	33272.207	67346.4	69911.3	Robustness
Z (1996-2003)	3	7		4430	401	33272.376	67346.8	69911.6	Robustness
Z (1996-2003)	3	8		4430	401	33272.350	67346.7	69911.6	Robustness
Z (1996-2003)	3	9		4430	401	33363.489	67529.0	70093.8	Robustness
Z (1996-2003)	3	10		4430	401	33272.353	67346.7	69911.6	Robustness

NOTE.—The table reports model-selection statistics for the benchmark sequential model across all available cached random starting seeds. Within each cohort and number of unobserved heterogeneity types, “Selected” marks the cached estimate with the lowest minimized negative log-likelihood. N_p is the number of estimated model parameters, including the $K - 1$ free type probabilities. AIC is computed as $2N_p + 2\ell$ and BIC as $\log(N)N_p + 2\ell$, where ℓ is the minimized negative log-likelihood. The baseline specification uses two unobserved types; the three-type specification is reported as a robustness check.

Table 27: Goodness of fit

	M (1987-1995)				Z (1996-2003)			
	Observed	Simulated	SE	95 CI	Observed	Simulated	SE	95 CI
Grade repetition (Primary education)	0.069	0.070	0.005	[0.060 0.079]	0.079	0.081	0.005	[0.071 0.092]
School recommendation	2.809	2.830	0.022	[2.786 2.874]	2.453	2.444	0.021	[2.403 2.486]
Grade repetition (Secondary education)	0.153	0.156	0.009	[0.138 0.173]	0.133	0.133	0.008	[0.117 0.148]
Secondary education enrollment	2.262	2.266	0.014	[2.238 2.294]	2.241	2.235	0.016	[2.204 2.267]
Work experience at age 17	0.379	0.380	0.009	[0.362 0.398]	0.241	0.243	0.008	[0.227 0.259]
Cognitive test available	0.382	0.382	0.010	[0.363 0.402]	0.379	0.384	0.010	[0.364 0.403]
Cognitive skills (θ^{cog})	0.163	0.162	0.027	[0.109 0.214]	-0.183	-0.195	0.029	[-0.252 -0.138]
Diligence skills (θ^{dil})	-0.085	-0.086	0.011	[-0.108 -0.064]	0.095	0.126	0.013	[0.100 0.152]
Social skills (θ^{soc})	0.011	0.013	0.013	[-0.012 0.038]	-0.013	0.024	0.012	[0.001 0.047]
Secondary education diploma	2.999	3.050	0.028	[2.995 3.105]	2.736	2.766	0.036	[2.696 2.836]
Tertiary education enrollment	0.575	0.573	0.019	[0.535 0.611]	0.329	0.333	0.016	[0.303 0.364]
Tertiary education diploma	0.759	0.760	0.020	[0.721 0.799]	0.443	0.457	0.035	[0.389 0.525]
Wage (first job) observed	0.697	0.706	0.016	[0.676 0.737]	0.540	0.549	0.018	[0.513 0.585]
Log hourly wage (first job)	1.679	1.656	0.021	[1.615 1.697]	1.687	1.702	0.029	[1.644 1.759]

NOTE.- Demographic cohort M includes individuals born between 1987 and 1995, while demographic cohort Z includes individuals born between 1996 and 2003.

Table 28: Schooling phase results (Cohort M)

	Grade repetition (PE)		School recommendation		Grade repetition (SE)		SE enrollment		Work experience age 17	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	-1.945***	(0.486)			-2.747***	(0.422)			-0.723***	(0.258)
Female	-0.556***	(0.119)	0.259***	(0.056)	-0.558***	(0.099)	0.453***	(0.085)	-0.114*	(0.061)
Migration background	0.394***	(0.147)	-0.104	(0.073)	0.138	(0.109)	-0.039	(0.090)	-0.424***	(0.088)
Born in Germany	0.274	(0.238)	0.319**	(0.129)	0.552**	(0.222)	-0.405**	(0.177)	-0.060	(0.149)
Number of siblings	0.200***	(0.036)	-0.070***	(0.021)	-0.007	(0.033)	-0.001	(0.030)	0.084***	(0.023)
Father education	-1.229***	(0.333)	0.403***	(0.104)	0.030	(0.155)	1.148***	(0.135)	0.038	(0.109)
Mother education	-0.477*	(0.271)	0.813***	(0.100)	0.016	(0.148)	0.541***	(0.129)	-0.086	(0.104)
Father tertiary education	-0.065	(0.314)	0.531***	(0.113)	0.210	(0.183)	0.330**	(0.165)	-0.073	(0.113)
Mother tertiary education	-0.234	(0.348)	0.337***	(0.127)	0.220	(0.193)	0.597***	(0.180)	0.093	(0.123)
Father occupation	-0.239*	(0.123)	0.347***	(0.057)	-0.147	(0.092)	0.219***	(0.076)	-0.083	(0.063)
Mother occupation	-0.634***	(0.157)	0.351***	(0.061)	-0.273***	(0.099)	0.614***	(0.078)	0.038	(0.067)
Big or mid-sized city	0.292**	(0.120)	0.003	(0.056)	0.154*	(0.084)	0.170**	(0.068)	-0.195***	(0.063)
West Germany	-0.320	(0.229)	0.671***	(0.118)	0.173	(0.178)	-0.465***	(0.116)	0.203*	(0.108)
Unemployment rate (<i>t</i> -specific)	-0.010	(0.022)	0.065***	(0.011)	-0.002	(0.015)	-0.043***	(0.010)	-0.007	(0.009)
Unobserved type 2	-1.119***	(0.130)	-0.151***	(0.054)	0.922***	(0.085)	1.608***	(0.072)	-0.572***	(0.064)

NOTE.- For the sake of brevity, this table reports only the effects of exogenous variables and omits the impact of endogenous variables, which are discussed in other figures and tables throughout the paper. The full results for the schooling phase are available upon request. School recommendation and secondary education (SE) enrollment are modeled using ordered logit. Abbreviations: PE for primary education, SE for secondary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

B.4: Model estimates

Table 29: Schooling phase results (Cohort Z)

	Grade repetition (PE)		School recommendation		Grade repetition (SE)		SE enrollment		Work experience age 17	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	-2.607***	(0.389)			-2.348***	(0.331)			-1.063***	(0.231)
Female	-0.347***	(0.116)	0.198***	(0.064)	-0.101	(0.104)	0.453***	(0.082)	-0.150**	(0.072)
Migration background	-0.035	(0.142)	-0.028	(0.078)	0.106	(0.114)	0.008	(0.085)	-0.251**	(0.098)
Born in Germany	0.887***	(0.233)	1.484***	(0.126)	0.746***	(0.185)	2.999***	(0.145)	0.435***	(0.158)
Number of siblings	0.211***	(0.032)	0.399***	(0.023)	0.067**	(0.034)	-0.106***	(0.031)	0.046*	(0.024)
Father education	-0.822***	(0.271)	0.591***	(0.107)	0.090	(0.160)	0.665***	(0.123)	0.063	(0.121)
Mother education	-0.866***	(0.271)	0.697***	(0.103)	-0.290*	(0.163)	0.665***	(0.120)	0.124	(0.116)
Father tertiary education	0.056	(0.265)	0.251**	(0.118)	0.115	(0.182)	0.369**	(0.146)	-0.079	(0.130)
Mother tertiary education	-0.407	(0.332)	0.414***	(0.124)	0.225	(0.191)	0.388**	(0.153)	-0.162	(0.135)
Father occupation	-0.418***	(0.134)	0.593***	(0.068)	-0.183*	(0.107)	-0.098	(0.081)	-0.088	(0.080)
Mother occupation	-0.252*	(0.144)	0.753***	(0.071)	-0.008	(0.112)	0.194**	(0.083)	0.013	(0.083)
Big or mid-sized city	0.055	(0.129)	0.737***	(0.067)	0.277***	(0.102)	-0.186**	(0.075)	-0.310***	(0.083)
West Germany	-0.236	(0.194)	0.862***	(0.114)	-0.065	(0.152)	0.347***	(0.093)	-0.071	(0.104)
Unemployment rate (<i>t</i> -specific)	-0.015	(0.020)	0.112***	(0.011)	-0.059**	(0.024)	0.034**	(0.015)	-0.045***	(0.017)
Unobserved type 2	-0.334**	(0.132)	-0.536***	(0.067)	0.466***	(0.094)	0.212***	(0.071)	-0.316***	(0.081)

NOTE.- For the sake of brevity, this table reports only the effects of exogenous variables and omits the impact of endogenous variables, which are discussed in other figures and tables throughout the paper. The full results for the schooling phase are available upon request. School recommendation and secondary education (SE) enrollment are modeled using ordered logit. Abbreviations: PE for primary education, SE for secondary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 30: Multidimensional skills functions (Cohort M)

	Cognitive skill selection		Cognitive skill (θ^{cog})		Diligence skill (θ^{dil})		Social skill (θ^{soc})	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	-0.820***	(0.261)	-0.891***	(0.190)	-0.085	(0.109)	-0.265**	(0.108)
Female	-0.076	(0.060)	-0.128**	(0.054)	0.088***	(0.034)	-0.025	(0.034)
Migration background	0.176**	(0.083)	-0.192***	(0.049)	0.030	(0.032)	0.039	(0.032)
Born in Germany	0.876***	(0.158)	0.284**	(0.143)	0.060	(0.074)	0.122*	(0.074)
Number of siblings	0.022	(0.023)	0.034*	(0.020)	0.053***	(0.012)	0.055***	(0.012)
Father education	0.143	(0.109)	0.043	(0.066)	0.042	(0.041)	-0.010	(0.041)
Mother education	0.315***	(0.104)	0.241***	(0.060)	-0.079**	(0.039)	-0.030	(0.039)
Father tertiary education	0.052	(0.113)	-0.046	(0.087)	-0.072	(0.054)	0.001	(0.054)
Mother tertiary education	-0.347***	(0.125)	-0.230***	(0.086)	-0.038	(0.053)	-0.033	(0.053)
Father high-skill occupation	0.132**	(0.062)	0.067	(0.043)	0.037	(0.027)	-0.035	(0.027)
Mother high-skill occupation	0.034	(0.067)	0.127***	(0.044)	-0.028	(0.028)	0.038	(0.027)
Big or mid-sized city	-0.111*	(0.062)	-0.073*	(0.038)	-0.018	(0.023)	-0.043*	(0.023)
West Germany	-0.054	(0.107)	0.066	(0.065)	0.008	(0.040)	0.057	(0.040)
Unemployment rate (t -specific)	-0.017*	(0.009)	0.012**	(0.006)	-0.010***	(0.004)	-0.013***	(0.004)
Delay (Secondary education)	-0.001	(0.086)	-0.097	(0.130)	-0.120	(0.073)	0.271***	(0.073)
Intermediate SE track	-0.111	(0.088)	0.601***	(0.053)	0.308***	(0.034)	0.460***	(0.034)
Upper SE track	-0.201**	(0.099)	1.289***	(0.107)	0.547***	(0.062)	0.761***	(0.062)
Work experience at age 17	-0.180***	(0.063)	0.063*	(0.038)	-0.060**	(0.023)	0.220***	(0.023)
Delay (Primary education) \times Female			-0.245*	(0.144)	-0.157*	(0.088)	-0.181**	(0.088)
\times Migration background			-0.093	(0.379)	-0.247	(0.168)	0.132	(0.167)
\times Number of siblings			-0.166***	(0.046)	-0.073***	(0.024)	-0.035	(0.024)
\times Both parents tertiary education			0.303	(0.255)	0.094	(0.178)	0.121	(0.177)
\times Both parents high-skill occupations			0.039	(0.126)	-0.033	(0.079)	-0.128	(0.078)
Upper SE track \times Female			0.003	(0.076)	0.095**	(0.047)	0.081*	(0.047)
\times Migration background			0.273	(0.208)	0.101	(0.103)	0.040	(0.103)
\times Number of siblings			-0.032	(0.032)	-0.028	(0.018)	-0.013	(0.018)
\times Both parents tertiary education			0.109	(0.099)	0.129**	(0.061)	0.094	(0.060)
\times Both parents high-skill occupations			0.015	(0.084)	-0.005	(0.049)	0.093*	(0.049)
Delay (Secondary education) \times Female			0.077	(0.108)	0.115*	(0.065)	0.075	(0.064)
\times Migration background			0.659*	(0.371)	-0.032	(0.139)	0.011	(0.138)
\times Number of siblings			0.019	(0.044)	-0.014	(0.024)	-0.038	(0.024)
\times Both parents tertiary education			0.144	(0.153)	0.097	(0.087)	-0.088	(0.087)
\times Both parents high-skill occupations			-0.052	(0.107)	0.032	(0.064)	0.009	(0.064)
Unobserved type 2	-0.396***	(0.063)	-0.463***	(0.039)	-0.816***	(0.024)	-0.946***	(0.024)

NOTE.- Abbreviations: SE for secondary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 31: Multidimensional skills functions (Cohort Z)

	Cognitive skill selection		Cognitive skill (θ^{cog})		Diligence skill (θ^{dil})		Social skill (θ^{soc})	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	-2.000***	(0.197)	-1.068***	(0.154)	1.022***	(0.089)	0.244***	(0.077)
Female	-0.093	(0.064)	-0.090	(0.060)	0.150***	(0.042)	-0.067*	(0.037)
Migration background	0.849***	(0.085)	-0.157***	(0.050)	0.145***	(0.038)	0.196***	(0.033)
Born in Germany	1.061***	(0.125)	0.138	(0.103)	-0.667***	(0.065)	-0.112**	(0.056)
Number of siblings	0.037*	(0.021)	0.049**	(0.019)	-0.016	(0.014)	0.027**	(0.012)
Father education	-0.154	(0.110)	0.062	(0.067)	-0.094*	(0.049)	0.023	(0.043)
Mother education	-0.147	(0.107)	0.166**	(0.066)	0.123**	(0.048)	0.076*	(0.041)
Father tertiary education	-0.070	(0.114)	0.207**	(0.086)	0.130**	(0.060)	0.013	(0.052)
Mother tertiary education	0.395***	(0.118)	0.123	(0.085)	-0.067	(0.061)	0.084	(0.053)
Father high-skill occupation	0.216***	(0.072)	0.173***	(0.049)	0.048	(0.037)	-0.083***	(0.032)
Mother high-skill occupation	0.255***	(0.075)	0.148***	(0.051)	0.029	(0.038)	0.115***	(0.033)
Big or mid-sized city	-0.008	(0.071)	0.015	(0.044)	0.013	(0.032)	0.084***	(0.028)
West Germany	0.078	(0.093)	-0.012	(0.060)	-0.071*	(0.041)	0.048	(0.035)
Unemployment rate (<i>t</i> -specific)	0.026*	(0.015)	0.006	(0.009)	-0.022***	(0.007)	-0.019***	(0.006)
Delay (Secondary education)	0.164*	(0.094)	-0.079	(0.116)	-0.370***	(0.085)	-0.017	(0.074)
Intermediate SE track	0.185*	(0.099)	0.457***	(0.059)	0.104**	(0.045)	0.170***	(0.039)
Upper SE track	-0.076	(0.105)	1.321***	(0.099)	0.132*	(0.070)	0.280***	(0.060)
Work experience at age 17	-0.228***	(0.076)	-0.033	(0.048)	-0.040	(0.033)	0.084***	(0.029)
Delay (Primary education) × Female			-0.344**	(0.136)	0.042	(0.101)	0.079	(0.087)
× Migration background			0.163	(0.211)	-0.794***	(0.200)	-0.285*	(0.173)
× Number of siblings			-0.092***	(0.032)	-0.057**	(0.025)	-0.042*	(0.021)
× Both parents tertiary education			0.123	(0.301)	0.289	(0.196)	-0.130	(0.170)
× Both parents high-skill occupations			-0.430***	(0.138)	-0.243**	(0.103)	-0.140	(0.089)
Upper SE track × Female			-0.006	(0.084)	0.215***	(0.059)	0.095*	(0.051)
× Migration background			-0.017	(0.154)	-0.752***	(0.122)	-0.287***	(0.105)
× Number of siblings			-0.075**	(0.031)	0.018	(0.021)	-0.022	(0.018)
× Both parents tertiary education			-0.117	(0.104)	0.052	(0.074)	0.009	(0.064)
× Both parents high-skill occupations			-0.172**	(0.085)	-0.205***	(0.061)	0.047	(0.053)
Delay (Secondary education) × Female			0.177	(0.115)	0.148*	(0.086)	0.066	(0.074)
× Migration background			-0.109	(0.170)	-0.598***	(0.143)	-0.390***	(0.124)
× Number of siblings			-0.063*	(0.035)	0.020	(0.026)	0.028	(0.023)
× Both parents tertiary education			-0.111	(0.147)	-0.069	(0.110)	-0.097	(0.095)
× Both parents high-skill occupations			0.078	(0.115)	0.072	(0.086)	0.105	(0.075)
Unobserved type 2	-0.415***	(0.071)	-0.071	(0.046)	-1.029***	(0.031)	-1.415***	(0.027)

NOTE.- Abbreviations: SE for secondary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 32: School-to-work transition phase results (Cohort M)

	SE diploma		TE enrollment		TE diploma	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant			-0.110	(0.470)	4.222***	(0.900)
Female	0.265***	(0.093)	-0.025	(0.109)	0.542***	(0.174)
Migration background	-0.021	(0.122)	-0.260*	(0.144)	-0.959***	(0.237)
Born in Germany	-0.025	(0.257)	0.306	(0.312)	0.174	(0.507)
Number of siblings	-0.134***	(0.038)	-0.000	(0.045)	-0.079	(0.077)
Father education	0.896***	(0.182)	-0.231	(0.206)	0.105	(0.258)
Mother education	0.101	(0.161)	0.053	(0.183)	-0.223	(0.247)
Father tertiary education	-0.171	(0.192)	-0.003	(0.212)	-0.444*	(0.252)
Mother tertiary education	0.336	(0.209)	0.143	(0.232)	-0.411	(0.277)
Father occupation	0.198**	(0.095)	0.047	(0.110)	0.289	(0.179)
Mother occupation	0.197*	(0.105)	0.172	(0.121)	-0.109	(0.181)
Big or mid-sized city	0.128	(0.097)	-0.230**	(0.113)	-0.151	(0.175)
West Germany	-0.253	(0.156)	-0.126	(0.181)	-0.490*	(0.294)
Unemployment rate (<i>t</i> -specific)	-0.000	(0.016)	-0.014	(0.018)	-0.031	(0.029)
Delay (secondary education)	-0.531***	(0.179)	-0.058	(0.153)	-0.341	(0.294)
Work experience at age 17	0.095	(0.098)	0.010	(0.114)	0.190	(0.181)
Cognitive skills (θ^{cog})	0.789***	(0.056)	0.131*	(0.067)	-0.125	(0.114)
Diligence skills (θ^{dil})	0.367***	(0.055)	0.036	(0.064)	-0.161	(0.121)
Social skills (θ^{soc})	0.422***	(0.057)	-0.204***	(0.066)	0.219*	(0.118)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.018	(0.052)	0.016	(0.061)	0.016	(0.107)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	0.069	(0.054)	0.013	(0.063)	-0.177*	(0.103)
Unobserved type 2	2.067***	(0.119)	-0.852***	(0.143)	0.033	(0.217)

NOTE.- For the sake of brevity, this table reports only the effects of exogenous variables and omits the impact of endogenous variables, which are discussed in other figures and tables throughout the paper. The full results for the schooling phase are available upon request. Abbreviations: PE for primary education, SE for secondary education, TE for tertiary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 33: School-to-work transition phase results (Cohort Z)

	SE diploma		TE enrollment		TE diploma	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant			-1.286***	(0.487)	4.716***	(1.195)
Female	0.414***	(0.094)	0.132	(0.134)	0.405	(0.271)
Migration background	0.179	(0.116)	-0.266	(0.165)	-1.078***	(0.361)
Born in Germany	0.312*	(0.168)	0.556**	(0.283)	-0.842	(0.638)
Number of siblings	0.091***	(0.030)	0.087*	(0.047)	-0.123	(0.106)
Father education	0.645***	(0.158)	0.102	(0.199)	0.017	(0.366)
Mother education	0.169	(0.158)	-0.172	(0.203)	-0.144	(0.386)
Father tertiary education	0.206	(0.172)	0.258	(0.215)	0.002	(0.403)
Mother tertiary education	0.440**	(0.171)	0.198	(0.215)	-1.052**	(0.434)
Father occupation	0.454***	(0.104)	0.015	(0.143)	-0.224	(0.280)
Mother occupation	0.576***	(0.109)	-0.117	(0.148)	-0.032	(0.288)
Big or mid-sized city	0.539***	(0.102)	0.124	(0.143)	-0.433	(0.281)
West Germany	-0.002	(0.136)	0.044	(0.196)	-0.067	(0.403)
Unemployment rate (<i>t</i> -specific)	0.015	(0.024)	-0.034	(0.034)	0.036	(0.068)
Delay (secondary education)	-0.456***	(0.161)	-0.405*	(0.211)	-0.271	(0.464)
Work experience at age 17	-0.156	(0.111)	0.174	(0.158)	0.357	(0.319)
Cognitive skills (θ^{cog})	0.422***	(0.054)	0.406***	(0.082)	-0.255	(0.175)
Diligence skills (θ^{dil})	-0.043	(0.053)	0.016	(0.073)	-0.084	(0.151)
Social skills (θ^{soc})	-0.016	(0.058)	-0.168**	(0.081)	-0.437***	(0.169)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.022	(0.046)	-0.128*	(0.075)	0.066	(0.172)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	0.044	(0.048)	-0.022	(0.072)	0.207	(0.165)
Unobserved type 2	-0.511***	(0.138)	-0.883***	(0.210)	-1.886***	(0.479)

NOTE.- For the sake of brevity, this table reports only the effects of exogenous variables and omits the impact of endogenous variables, which are discussed in other figures and tables throughout the paper. The full results for the schooling phase are available upon request. Abbreviations: PE for primary education, SE for secondary education, TE for tertiary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 34: Selection equation and log-hourly wage function (Cohort M)

	Wage selection equation		Log-hourly wage (first job)	
	Coeff.	SE	Coeff.	SE
Constant	-1.872***	(0.549)	0.991***	(0.168)
Female	-0.122	(0.128)	-0.014	(0.031)
Migration background	-0.139	(0.162)	-0.022	(0.043)
Born in Germany	0.014	(0.325)	0.155*	(0.094)
Number of siblings	0.124**	(0.052)	-0.005	(0.013)
Father education	0.007	(0.228)	0.007	(0.058)
Mother education	-0.002	(0.205)	0.028	(0.052)
Father tertiary education	-0.618***	(0.232)	0.025	(0.061)
Mother tertiary education	-0.311	(0.248)	0.045	(0.067)
Father occupation	0.017	(0.130)	0.015	(0.032)
Mother occupation	-0.090	(0.143)	0.018	(0.035)
Big or mid-sized city	0.017	(0.130)	0.018	(0.033)
West Germany	-0.015	(0.212)	0.132***	(0.046)
Unemployment rate (<i>t</i> -specific)	0.018	(0.022)	-0.022***	(0.006)
Delay (Secondary education)	0.040	(0.175)	-0.074	(0.046)
Work experience at age 17	0.369***	(0.137)	0.070**	(0.032)
Cognitive skills (θ^{cog})	-0.336***	(0.077)	0.064*	(0.035)
Diligence skills (θ^{dil})	-0.176**	(0.074)	0.019	(0.036)
Social skills (θ^{soc})	-0.104	(0.077)	0.030	(0.035)
Cognitive skills (θ^{cog}) × Diligence skills (θ^{dil})	-0.082	(0.067)	-0.028	(0.020)
Cognitive skills (θ^{cog}) × Social skills (θ^{soc})	0.057	(0.071)	-0.005	(0.021)
Tertiary education enrollment × Cognitive skills (θ^{cog})			0.024	(0.053)
× Diligence skills (θ^{dil})			0.071	(0.049)
× Social skills (θ^{soc})			-0.043	(0.050)
Tertiary education diploma × Intermediate secondary education			0.113	(0.092)
× Upper secondary education			0.146	(0.108)
TE dipl. × Intermediate SE × Cognitive skills (θ^{cog})			-0.012	(0.058)
TE dipl. × Upper SE × Cognitive skills (θ^{cog})			-0.018	(0.061)
TE dipl. × Intermediate SE × Diligence skills (θ^{dil})			-0.028	(0.051)
TE dipl. × Upper SE × Diligence skills (θ^{dil})			0.046	(0.057)
TE dipl. × Intermediate SE × Social skills (θ^{soc})			0.076	(0.053)
TE dipl. × Upper SE × Social skills (θ^{soc})			0.009	(0.057)
Lower secondary education	1.996***	(0.274)	0.130	(0.121)
Intermediate secondary education	2.028***	(0.251)	0.136	(0.116)
Upper secondary education	2.743***	(0.300)	0.209*	(0.126)
Tertiary education enrollment	0.217	(0.192)	0.407***	(0.071)
Tertiary education diploma	3.038***	(0.263)	0.039	(0.112)
Unobserved type 2	-0.725***	(0.166)	0.116***	(0.042)
Unobserved type 2 × Cognitive skills (θ^{cog})			-0.068*	(0.040)
Unobserved type 2 × Diligence skills (θ^{dil})			-0.070*	(0.038)
Unobserved type 2 × Social skills (θ^{soc})			-0.002	(0.037)

NOTE.- Abbreviations: PE for primary education, SE for secondary education, TE for tertiary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 35: Selection equation and log-hourly wage function (Cohort Z)

Endogenous t	Wage selection equation		Log-hourly wage (first job)	
	Coeff.	SE	Coeff.	SE
Constant	-1.074***	(0.390)	1.439***	(0.148)
Female	-0.241**	(0.115)	0.005	(0.048)
Migration background	-0.105	(0.140)	0.110*	(0.058)
Born in Germany	0.050	(0.203)	0.016	(0.089)
Number of siblings	0.080**	(0.038)	-0.028*	(0.016)
Father education	-0.272	(0.183)	0.055	(0.075)
Mother education	-0.144	(0.181)	-0.107	(0.079)
Father tertiary education	-0.029	(0.193)	-0.103	(0.083)
Mother tertiary education	-0.071	(0.191)	-0.107	(0.086)
Father occupation	0.163	(0.125)	0.035	(0.051)
Mother occupation	0.043	(0.131)	-0.095*	(0.053)
Big or mid-sized city	-0.008	(0.123)	0.022	(0.050)
West Germany	-0.060	(0.165)	-0.013	(0.067)
Unemployment rate (t -specific)	-0.038	(0.029)	0.012	(0.009)
Delay (Secondary education)	-0.017	(0.158)	0.024	(0.068)
Work experience at age 17	-0.162	(0.138)	0.102*	(0.057)
Cognitive skills (θ^{cog})	-0.180***	(0.067)	0.053	(0.039)
Diligence skills (θ^{dil})	-0.147**	(0.063)	0.006	(0.035)
Social skills (θ^{soc})	-0.085	(0.069)	0.053	(0.039)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.005	(0.055)	0.054**	(0.027)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.037	(0.056)	0.001	(0.029)
Tertiary education enrollment \times Cognitive skills (θ^{cog})			-0.014	(0.070)
\times Diligence skills (θ^{dil})			0.007	(0.067)
\times Social skills (θ^{soc})			-0.040	(0.062)
Tertiary education diploma \times Intermediate secondary education			0.037	(0.157)
\times Upper secondary education			-0.169	(0.190)
TE dipl. \times Intermediate SE \times Cognitive skills (θ^{cog})			0.096	(0.106)
TE dipl. \times Upper SE \times Cognitive skills (θ^{cog})			-0.045	(0.136)
TE dipl. \times Intermediate SE \times Diligence skills (θ^{dil})			-0.026	(0.097)
TE dipl. \times Upper SE \times Diligence skills (θ^{dil})			0.090	(0.124)
TE dipl. \times Intermediate SE \times Social skills (θ^{soc})			0.099	(0.095)
TE dipl. \times Upper SE \times Social skills (θ^{soc})			0.017	(0.126)
Lower secondary education	1.545***	(0.217)	0.021	(0.122)
Intermediate secondary education	1.873***	(0.180)	0.021	(0.108)
Upper secondary education	2.078***	(0.226)	0.143	(0.124)
Tertiary education enrollment	0.194	(0.186)	0.224***	(0.084)
Tertiary education diploma	2.366***	(0.354)	0.281*	(0.164)
Unobserved type 2	-0.933***	(0.167)	0.304***	(0.099)
Unobserved type 2 \times Cognitive skills (θ^{cog})			-0.004	(0.077)
Unobserved type 2 \times Diligence skills (θ^{dil})			0.019	(0.062)
Unobserved type 2 \times Social skills (θ^{soc})			0.203***	(0.067)

NOTE.- Abbreviations: PE for primary education, SE for secondary education, TE for tertiary education. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

C: Results

Table 36: Simplified-model first-stage checks: reform exposure, recommendations, and academic track enrolment

	(1)	(2)	(3)	(4)	(5)
	Academic recommendation	Academic enrolment	Academic enrolment	Academic enrolment	Academic enrolment
Binding School Recommendation	0.013 (0.009)	-0.001 (0.010)		-0.007 (0.009)	0.000 (0.011)
Academic recommendation			0.466*** (0.011)	0.466*** (0.011)	0.475*** (0.013)
Academic recommendation × binding regime					-0.020 (0.017)
Dependent-variable mean	0.343	0.430	0.430	0.430	0.430
Observations	9361	9361	9361	9361	9361
R ²	0.180	0.187	0.351	0.351	0.351

NOTE.—The table reports linear probability model checks corresponding to the simplified model. Academic recommendation equals one for an upper-track recommendation and zero otherwise. Academic track enrolment equals one for upper-secondary academic track enrolment and zero otherwise. Columns (1) and (2) estimate the association between exposure to a binding recommendation regime and, respectively, academic recommendations and academic track enrolment. Columns (3)–(5) estimate the relationship between academic recommendations and academic track enrolment; column (4) additionally controls for exposure to a binding recommendation regime, and column (5) allows the recommendation-enrolment relationship to differ in binding regimes. All columns control for gender, migration background, being born in Germany, number of siblings, parental education, parental occupational position, city residence, and West German origin. The table documents the two first-stage margins used in the simplified model, $Z_i^p \rightarrow R_i$ and $R_i \rightarrow S_i$, and the reduced-form relationship $Z_i^p \rightarrow S_i$. Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Figure 11: Cognitive skills development, school recommendations and school enrolment

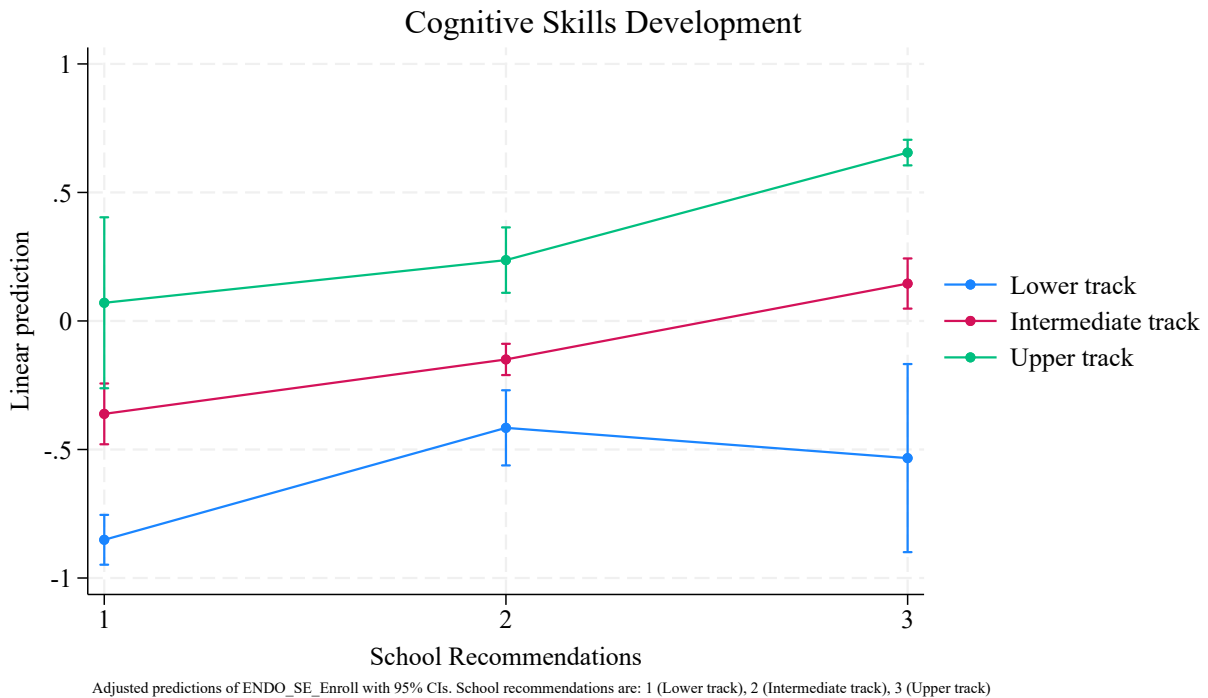


Table 37: First stage: Binding recommendation reforms, school recommendations, and track enrolment

	(1)	(2)	(3)	(4)	(5)	(6)
	Rec.: Lower	Rec.: Intermediate	Rec.: Upper	Enrol.: Lower	Enrol.: Intermediate	Enrol.: Upper
Binding School Recommendation	0.018* (0.007)	-0.021* (0.009)	0.013 (0.009)	-0.004 (0.007)	0.008 (0.010)	-0.001 (0.010)
Mean in non-binding regime	0.126	0.247	0.339	0.150	0.382	0.433
Observations	9361	9361	9361	9361	9361	9361
R ²	0.070	0.034	0.180	0.069	0.066	0.187

NOTE.—The table reports linear probability model estimates of the relationship between exposure to a binding school recommendation regime and early tracking outcomes. Columns (1)–(3) use indicators for receiving a lower-, intermediate-, or upper-track recommendation as dependent variables. Columns (4)–(6) use indicators for enrolment in the corresponding secondary school track as dependent variables. Each column controls for gender, migration background, being born in Germany, number of siblings, parental education, parental occupational position, city residence, and West German origin. The row “Mean in non-binding regime” reports the dependent-variable mean among students in the estimation sample exposed to a non-binding recommendation regime. Robust standard errors are reported in parentheses. In the model, this table documents the first-stage relationship between the institutional recommendation regime and the recommendation/enrolment margins used in the identification argument. The exclusion restriction maintained in the model is that, conditional on observed characteristics and latent type, the binding recommendation regime affects later skills, higher education, and wages only through school recommendations and realised track enrolment. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 38: First-Stage: Binding recommendation reforms and school recommendations

	(1)	All (2)	(3)	(4)	M (1987-1995) (5)	(6)	(7)	Z (1996-2003) (8)	(9)
	Lower track recommenda- tion	Intermediate track recom- mendation	Upper track recommenda- tion	Lower track recommenda- tion	Intermediate track recom- mendation	Upper track recommenda- tion	Lower track recommenda- tion	Intermediate track recom- mendation	Upper track recommenda- tion
Binding recommendation regime	0.018* (0.007)	-0.021* (0.009)	0.013 (0.009)	0.005 (0.013)	-0.021 (0.017)	-0.011 (0.017)	0.026** (0.009)	-0.015 (0.012)	0.026* (0.013)

NOTE.—The table reports category-specific linear probability model first-stage estimates of the relationship between exposure to a binding recommendation regime and school recommendations. Columns (1)–(3) use all cohorts, columns (4)–(6) use the M cohort, and columns (7)–(9) use the Z cohort. The M cohort is defined by birth years 1987–1995 and the Z cohort by birth years 1996–2003. All specifications include the baseline controls used in the main paper: gender, migration background, being born in Germany, number of siblings, parental education, parental occupational position, city residence, and West German origin. Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 39: School Recommendations and Binding Reforms

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

NOTE.—The table reports first-stage evidence on the relationship between binding recommendation regimes, the alignment between school recommendations and realised enrolment, and secondary school track enrolment. Each column corresponds to a separate enrolment outcome. Standard errors are reported in parentheses. The omitted category is students for whom the school recommendation equals realised enrolment under a binding recommendation regime. The F-statistics test the joint relevance of the recommendation-regime indicators for the corresponding enrolment outcome. Binding reforms are interpreted as quasi-experimental variation in the early tracking environment: conditional on observed characteristics, they are assumed to be uncorrelated with latent endowments η_i and to affect later skills, higher education, and wages only through school recommendations and realised track enrolment. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 40: First-Stage: School Recommendation and School enrolment

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

NOTE.—The table reports first-stage estimates of the relationship between school recommendations and realised secondary school track enrolment. Each column corresponds to a separate enrolment outcome. Standard errors are reported in parentheses. The reported F-statistics test the relevance of the corresponding school recommendation for enrolment in the indicated track. School recommendations are not interpreted as randomly assigned instruments: they may be correlated with latent endowments η_i . In the model, their identifying role is to shift track enrolment conditional on observed characteristics and latent type, while being excluded from later skill, education, and wage outcomes except through realised track enrolment. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 41: Changes in returns to one standard deviation increase in measurement-invariant cognitive and dedicated non-cognitive skills across cohorts by skill bundle

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Z (1996-2003)	Changes across cohorts	M (1987-1995)	Z (1996-2003)	Changes across cohorts
Cognitive (θ^{cog}) \times Social skills (θ^{soc})							
$\theta^{cog} = -1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	-0.041 (0.028)	0.040 (0.042)	0.081** (0.035)	-0.023 (0.025)	0.033 (0.037)	0.056* (0.030)
$\theta^{cog} = -1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	-0.038 (0.030)	0.040 (0.040)	0.078** (0.038)	-0.023 (0.025)	0.033 (0.037)	0.056* (0.030)
$\theta^{cog} = 1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	-0.025 (0.031)	0.033 (0.041)	0.057 (0.037)	-0.005 (0.028)	0.027 (0.037)	0.032 (0.030)
$\theta^{cog} = 1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	-0.028 (0.034)	0.030 (0.038)	0.057 (0.040)	-0.005 (0.028)	0.027 (0.037)	0.032 (0.030)
Cognitive (θ^{cog}) \times Diligence skills (θ^{dil})							
$\theta^{cog} = -1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.053** (0.025)	-0.030 (0.048)	-0.084** (0.039)	0.050** (0.023)	-0.037 (0.046)	-0.087** (0.038)
$\theta^{cog} = -1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.057** (0.027)	-0.032 (0.051)	-0.089** (0.045)	0.050** (0.023)	-0.037 (0.046)	-0.087** (0.038)
$\theta^{cog} = 1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	-0.006 (0.032)	0.072 (0.049)	0.079* (0.042)	-0.019 (0.028)	0.076* (0.045)	0.095*** (0.036)
$\theta^{cog} = 1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	-0.007 (0.032)	0.074 (0.050)	0.081* (0.042)	-0.019 (0.028)	0.076* (0.045)	0.095*** (0.036)

NOTE.- The dependent variable is log hourly wages in the first job. Factors are constructed from the measurement-invariant cognitive factor and dedicated non-cognitive factors: cognitive skill is estimated from a trimmed age-17 item set with equal loadings across cohorts, while social and diligence skills are dedicated factors based on their corresponding non-cognitive item sets. The factors are standardized in the pooled sample before the cohort split. Skill bundles fix standardized factor scores at -1 or 1; returns to $\theta^{soc} + 1$ or $\theta^{dil} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

C.1: Returns to multidimensional skills bundle

Table 42: Changes in returns to one standard deviation increase in multidimensional skills across cohorts by skill bundle

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Z (1996-2003)	Changes across cohorts	M (1987-1995)	Z (1996-2003)	Changes across cohorts
Cognitive (θ^{cog}) \times Social (θ^{soc})							
$\theta^{cog} = -2 \times \theta^{soc} = -2$	$\theta^{soc} + 1$	0.041 (0.045)	0.074 (0.056)	0.033 (0.030)	0.029 (0.044)	0.084 (0.051)	0.055*** (0.017)
$\theta^{cog} = -2 \times \theta^{soc} = 2$	$\theta^{soc} + 1$	0.038 (0.047)	0.077 (0.049)	0.039 (0.027)	0.029 (0.044)	0.084 (0.051)	0.055*** (0.017)
$\theta^{cog} = 2 \times \theta^{soc} = -2$	$\theta^{soc} + 1$	0.033 (0.046)	0.075 (0.066)	0.042 (0.037)	0.015 (0.042)	0.091 (0.066)	0.076** (0.032)
$\theta^{cog} = 2 \times \theta^{soc} = 2$	$\theta^{soc} + 1$	-0.010 (0.045)	0.077 (0.068)	0.086** (0.039)	0.015 (0.042)	0.091 (0.066)	0.076** (0.032)
Cognitive (θ^{cog}) \times Diligence (θ^{dil})							
$\theta^{cog} = -2 \times \theta^{dil} = -2$	$\theta^{dil} + 1$	0.096** (0.045)	-0.081 (0.052)	-0.177*** (0.024)	0.092** (0.043)	-0.087* (0.050)	-0.180*** (0.015)
$\theta^{cog} = -2 \times \theta^{dil} = 2$	$\theta^{dil} + 1$	0.115** (0.049)	-0.076 (0.052)	-0.191*** (0.029)	0.092** (0.043)	-0.087* (0.050)	-0.180*** (0.015)
$\theta^{cog} = 2 \times \theta^{dil} = -2$	$\theta^{dil} + 1$	0.005 (0.048)	0.109 (0.072)	0.104** (0.040)	-0.027 (0.046)	0.121* (0.069)	0.149*** (0.030)
$\theta^{cog} = 2 \times \theta^{dil} = 2$	$\theta^{dil} + 1$	0.018 (0.050)	0.103 (0.074)	0.086* (0.044)	-0.027 (0.046)	0.121* (0.069)	0.149*** (0.030)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Skill bundles fix these standardized factor scores at the values shown in the first column; returns to $\theta^{soc} + 1$ or $\theta^{dil} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 43: Changes in returns to one standard deviation increase in cognitive and Big Five skills across cohorts by skill bundle

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Z (1996-2003)	Changes across cohorts	M (1987-1995)	Z (1996-2003)	Changes across cohorts
Cognitive (θ^{cog}) \times Extroversion (θ^{extr})							
$\theta^{cog} = -1 \times \theta^{extr} = -1$	$\theta^{extr} + 1$	-0.028 (0.036)	0.057* (0.031)	0.085*** (0.023)	-0.012 (0.033)	0.050* (0.028)	0.061*** (0.015)
$\theta^{cog} = -1 \times \theta^{extr} = 1$	$\theta^{extr} + 1$	-0.024 (0.038)	0.055* (0.031)	0.079*** (0.027)	-0.012 (0.033)	0.050* (0.028)	0.061*** (0.015)
$\theta^{cog} = 1 \times \theta^{extr} = -1$	$\theta^{extr} + 1$	-0.013 (0.033)	0.069* (0.039)	0.081*** (0.028)	-0.026 (0.031)	0.065* (0.037)	0.091*** (0.019)
$\theta^{cog} = 1 \times \theta^{extr} = 1$	$\theta^{extr} + 1$	-0.020 (0.034)	0.071** (0.036)	0.092*** (0.027)	-0.026 (0.031)	0.065* (0.037)	0.091*** (0.019)
Cognitive (θ^{cog}) \times Conscientiousness (θ^{cons})							
$\theta^{cog} = -1 \times \theta^{cons} = -1$	$\theta^{cons} + 1$	0.031 (0.038)	-0.029 (0.029)	-0.060** (0.026)	0.015 (0.033)	-0.043 (0.027)	-0.059*** (0.018)
$\theta^{cog} = -1 \times \theta^{cons} = 1$	$\theta^{cons} + 1$	0.044 (0.037)	-0.034 (0.031)	-0.078*** (0.028)	0.015 (0.033)	-0.043 (0.027)	-0.059*** (0.018)
$\theta^{cog} = 1 \times \theta^{cons} = -1$	$\theta^{cons} + 1$	0.003 (0.039)	0.060 (0.046)	0.057** (0.027)	-0.006 (0.034)	0.065 (0.043)	0.072*** (0.022)
$\theta^{cog} = 1 \times \theta^{cons} = 1$	$\theta^{cons} + 1$	0.004 (0.036)	0.065 (0.045)	0.061* (0.032)	-0.006 (0.034)	0.065 (0.043)	0.072*** (0.022)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors use the baseline age-17 cognitive factor and replace the baseline diligence and social factors with standardized Big Five conscientiousness and extroversion measures (ENDO_B5C and ENDO_B5E), standardized in the pooled sample before the cohort split. Skill bundles fix standardized factor scores at -1 or 1; returns to $\theta^{extr} + 1$ or $\theta^{cons} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 44: Changes in returns to one standard deviation increase in multidimensional skills across cohorts by skill bundle in the simplified model

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Z (1996-2003)	Changes across cohorts	M (1987-1995)	Z (1996-2003)	Changes across cohorts
Cognitive (θ^{cog}) \times Social (θ^{soc})							
$\theta^{cog} = -1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	0.016 (0.036)	0.045 (0.037)	0.030** (0.015)	0.030 (0.034)	0.045 (0.037)	0.015 (0.012)
$\theta^{cog} = -1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	0.019 (0.036)	0.048 (0.038)	0.029** (0.014)	0.030 (0.034)	0.045 (0.037)	0.015 (0.012)
$\theta^{cog} = 1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	-0.027 (0.034)	0.106** (0.049)	0.134*** (0.020)	-0.017 (0.034)	0.107** (0.050)	0.124*** (0.019)
$\theta^{cog} = 1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	-0.026 (0.035)	0.107** (0.050)	0.133*** (0.019)	-0.017 (0.034)	0.107** (0.050)	0.124*** (0.019)
Cognitive (θ^{cog}) \times Diligence (θ^{dil})							
$\theta^{cog} = -1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.038 (0.031)	-0.074** (0.034)	-0.111*** (0.012)	0.048 (0.031)	-0.071** (0.034)	-0.120*** (0.009)
$\theta^{cog} = -1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.037 (0.033)	-0.070** (0.035)	-0.107*** (0.013)	0.048 (0.031)	-0.071** (0.034)	-0.120*** (0.009)
$\theta^{cog} = 1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	-0.011 (0.035)	0.085* (0.051)	0.096*** (0.020)	-0.002 (0.034)	0.082 (0.051)	0.084*** (0.019)
$\theta^{cog} = 1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	-0.015 (0.037)	0.091* (0.052)	0.106*** (0.020)	-0.002 (0.034)	0.082 (0.051)	0.084*** (0.019)

NOTE.- The dependent variable is log hourly wages in the first job. The simplified model uses the same baseline age-17 cognitive, diligence, and social factors as the main specification. These factors are constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Skill bundles fix standardized factor scores at -1 or 1; returns to $\theta^{soc} + 1$ or $\theta^{dil} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold higher-education completion fixed, while total returns allow higher-education completion to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 45: Changes in returns to one standard deviation increase in multidimensional skills across cohorts by skill bundle, excluding younger Cohort Z birth years

Multidimensional skills bundle	Returns to:	Total			Direct		
		M (1987-1995)	Trimmed Z (1996-1998)	Changes across cohorts	M (1987-1995)	Trimmed Z (1996-1998)	Changes across cohorts
Cognitive (θ^{cog}) \times Social (θ^{soc})							
$\theta^{cog} = -1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	0.039 (0.030)	0.095** (0.045)	0.056* (0.031)	0.026 (0.027)	0.080** (0.038)	0.054*** (0.018)
$\theta^{cog} = -1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	0.034 (0.032)	0.080 (0.049)	0.046 (0.036)	0.026 (0.027)	0.080** (0.038)	0.054*** (0.018)
$\theta^{cog} = 1 \times \theta^{soc} = -1$	$\theta^{soc} + 1$	0.031 (0.028)	0.076 (0.047)	0.045 (0.036)	0.019 (0.026)	0.095** (0.044)	0.076*** (0.026)
$\theta^{cog} = 1 \times \theta^{soc} = 1$	$\theta^{soc} + 1$	0.016 (0.026)	0.112** (0.056)	0.096** (0.046)	0.019 (0.026)	0.095** (0.044)	0.076*** (0.026)
Cognitive (θ^{cog}) \times Diligence (θ^{dil})							
$\theta^{cog} = -1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.078*** (0.029)	-0.003 (0.044)	-0.081** (0.033)	0.062** (0.026)	-0.031 (0.036)	-0.093*** (0.016)
$\theta^{cog} = -1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.089*** (0.032)	-0.006 (0.043)	-0.095*** (0.031)	0.062** (0.026)	-0.031 (0.036)	-0.093*** (0.016)
$\theta^{cog} = 1 \times \theta^{dil} = -1$	$\theta^{dil} + 1$	0.033 (0.031)	0.105* (0.055)	0.072** (0.035)	0.002 (0.029)	0.095* (0.049)	0.093*** (0.024)
$\theta^{cog} = 1 \times \theta^{dil} = 1$	$\theta^{dil} + 1$	0.041 (0.032)	0.097* (0.056)	0.056 (0.036)	0.002 (0.029)	0.095* (0.049)	0.093*** (0.024)

NOTE.- The dependent variable is log hourly wages in the first job. Cohort M uses the benchmark sample, while trimmed Cohort Z includes individuals born between 1996 and 1998, excluding younger birth cohorts whose tertiary-degree outcomes may be right-censored by the 2020 observation window. The table uses the baseline age-17 cognitive, diligence, and social factors, constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Skill bundles fix standardized factor scores at -1 or 1; returns to $\theta^{soc} + 1$ or $\theta^{dil} + 1$ report a one-standard-deviation increase in the indicated dimension. Direct returns hold school-to-work transition choices fixed, while total returns allow these choices to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 46: Difference between total and direct returns to multidimensional skills

	M (1987-1995)		Z (1996-2003)		Direct - Total	
	Total	Direct	Total	Direct	M (1987-1995)	Z (1996-2003)
Aggregate skills	0.157*** (0.049)	0.061 (0.049)	0.222*** (0.069)	0.211*** (0.070)	-0.096*** (0.025)	-0.010 (0.018)
Cognitive skills (θ^{cog})	0.107*** (0.022)	0.045** (0.022)	0.098*** (0.031)	0.061* (0.033)	-0.062*** (0.016)	-0.037** (0.015)
Diligence skills (θ^{dil})	0.056** (0.024)	0.028 (0.019)	0.008 (0.026)	0.009 (0.024)	-0.028* (0.016)	0.002 (0.011)
Social skills (θ^{soc})	0.030 (0.023)	0.022 (0.018)	0.073** (0.029)	0.087*** (0.027)	-0.008 (0.016)	0.015 (0.011)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.026 (0.027)	-0.030 (0.020)	0.045 (0.032)	0.052* (0.027)	-0.004 (0.020)	0.007 (0.015)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.012 (0.025)	-0.004 (0.019)	-0.002 (0.029)	0.002 (0.026)	0.008 (0.018)	0.004 (0.015)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.051 (0.038)	-0.017 (0.030)	-0.089* (0.046)	-0.052 (0.043)	0.035 (0.023)	0.037* (0.019)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. The final columns test the difference between direct and total returns. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 47: Educational sorting: one standard deviation (σ) increase

	M (1987-1995)			Z (1996-2003)		
	Upper secondary education	Tertiary education enrollment	Tertiary education diploma	Upper secondary education	Tertiary education enrollment	Tertiary education diploma
Aggregate skills	0.186*** (0.013)	0.047*** (0.011)	0.004 (0.012)	0.062*** (0.022)	0.014 (0.013)	-0.004 (0.009)
Cognitive skills (θ^{cog})	0.099*** (0.010)	0.034*** (0.008)	0.012 (0.007)	0.071*** (0.014)	0.036*** (0.009)	0.009 (0.007)
Diligence skills (θ^{dil})	0.046*** (0.011)	0.014* (0.008)	0.001 (0.008)	-0.008 (0.015)	0.000 (0.007)	-0.001 (0.005)
Social skills (θ^{soc})	0.056*** (0.012)	-0.001 (0.009)	-0.001 (0.008)	-0.007 (0.015)	-0.010 (0.007)	-0.011** (0.005)

NOTE.- The dependent variables are the educational choices in the school-to-work transition period of the model. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills (ATE). Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 48: Wage returns to multidimensional skills by cohort (Robustness 1)

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.156*** (0.043)	0.052 (0.044)	0.222*** (0.065)	0.207*** (0.065)	0.067 (0.048)	0.155*** (0.047)
Cognitive skills (θ^{cog})	0.101*** (0.022)	0.040* (0.021)	0.092*** (0.032)	0.054* (0.032)	-0.009 (0.022)	0.014 (0.019)
Diligence skills (θ^{dil})	0.059** (0.024)	0.027 (0.018)	0.010 (0.028)	0.010 (0.026)	-0.049** (0.023)	-0.017 (0.016)
Social skills (θ^{soc})	0.029 (0.022)	0.019 (0.019)	0.073** (0.029)	0.087*** (0.027)	0.043 (0.027)	0.068*** (0.021)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.024 (0.025)	-0.031 (0.021)	0.046 (0.033)	0.053** (0.027)	0.070** (0.028)	0.084*** (0.014)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.011 (0.027)	-0.004 (0.021)	0.001 (0.030)	0.003 (0.027)	0.012 (0.026)	0.007 (0.014)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.044 (0.034)	-0.013 (0.029)	-0.082* (0.046)	-0.044 (0.043)	-0.039 (0.033)	-0.031 (0.024)

NOTE.- The dependent variable is log hourly wages in the first job. Robustness 1 replaces the baseline cognitive factor with a factor based only on age-17 SOEP cognitive-test items, excluding grades, advanced-course indicators, and parental-involvement indicators from the cognitive measurement system. Diligence and social skills use the baseline two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 49: Wage returns to multidimensional skills by cohort (Robustness 2)

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.166*** (0.042)	0.061 (0.043)	0.203*** (0.066)	0.199*** (0.065)	0.037 (0.047)	0.137*** (0.048)
Cognitive skills (θ^{cog})	0.103*** (0.022)	0.044** (0.021)	0.076** (0.032)	0.051 (0.031)	-0.027 (0.022)	0.007 (0.019)
Diligence skills (θ^{dil})	0.059** (0.023)	0.027 (0.018)	0.010 (0.027)	0.010 (0.026)	-0.049** (0.022)	-0.017 (0.016)
Social skills (θ^{soc})	0.030 (0.022)	0.018 (0.019)	0.070** (0.029)	0.084*** (0.027)	0.040 (0.027)	0.066*** (0.021)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.023 (0.025)	-0.030 (0.020)	0.045 (0.032)	0.051* (0.027)	0.067** (0.026)	0.081*** (0.013)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.002 (0.026)	0.002 (0.020)	0.003 (0.030)	0.003 (0.026)	0.005 (0.026)	0.001 (0.014)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.045 (0.034)	-0.018 (0.028)	-0.066 (0.046)	-0.041 (0.042)	-0.021 (0.032)	-0.023 (0.023)

NOTE.- The dependent variable is log hourly wages in the first job. Robustness 2 replaces the baseline cognitive factor with a cognitive-test-only factor computed within each age-17 survey year and then restandardized in the full sample; this excludes grades, advanced-course indicators, and parental-involvement indicators from the cognitive measurement system. Diligence and social skills use the baseline two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. "Aggregate skills" refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. "Direct" returns hold school-to-work transition choices fixed, while "Total" returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. "Changes across cohorts" are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 50: Wage returns to multidimensional skills by cohort (Robustness 3)

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.144** (0.057)	0.064 (0.054)	0.192** (0.079)	0.169** (0.081)	0.048 (0.051)	0.105** (0.051)
Cognitive skills (θ^{cog})	0.105*** (0.022)	0.045** (0.022)	0.092*** (0.032)	0.055 (0.033)	-0.013 (0.020)	0.010 (0.018)
Diligence skills (θ^{dil})	0.082*** (0.026)	0.046** (0.021)	0.018 (0.030)	0.013 (0.029)	-0.064*** (0.024)	-0.033* (0.018)
Social skills (θ^{soc})	-0.007 (0.025)	-0.004 (0.021)	0.028 (0.034)	0.038 (0.033)	0.035 (0.027)	0.042* (0.024)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.038 (0.030)	-0.039 (0.025)	0.075* (0.038)	0.082** (0.034)	0.113*** (0.029)	0.121*** (0.017)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	0.003 (0.032)	0.016 (0.025)	-0.022 (0.035)	-0.019 (0.033)	-0.026 (0.026)	-0.034** (0.015)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.027 (0.039)	0.001 (0.033)	-0.073 (0.050)	-0.042 (0.047)	-0.046 (0.030)	-0.043* (0.024)

NOTE.- The dependent variable is log hourly wages in the first job. Robustness 3 uses the baseline age-17 cognitive factor and replaces the baseline non-cognitive two-factor system with dedicated social and diligence factors, each estimated from its corresponding non-cognitive item set. The factors are standardized in the pooled sample before the cohort split. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 51: Wage returns to measurement-invariant cognitive and dedicated non-cognitive skills by cohort: direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.054 (0.050)	0.011 (0.044)	0.178** (0.080)	0.122* (0.071)	0.124* (0.074)	0.111* (0.061)
Cognitive skills (θ^{cog})	0.087*** (0.024)	0.034 (0.021)	0.080* (0.041)	0.025 (0.037)	-0.008 (0.036)	-0.009 (0.028)
Diligence skills (θ^{dil})	0.026 (0.021)	0.016 (0.017)	0.013 (0.042)	0.013 (0.039)	-0.013 (0.043)	-0.004 (0.037)
Social skills (θ^{soc})	-0.032 (0.023)	-0.014 (0.017)	0.034 (0.033)	0.030 (0.030)	0.066* (0.035)	0.044 (0.030)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.032 (0.026)	-0.035* (0.019)	0.054* (0.029)	0.056** (0.025)	0.086*** (0.023)	0.091*** (0.011)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	0.006 (0.024)	0.009 (0.019)	-0.003 (0.024)	-0.003 (0.022)	-0.009 (0.022)	-0.012** (0.006)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.002 (0.015)	-0.000 (0.000)	0.001 (0.016)	0.000 (0.000)	0.004 (0.021)	0.000 (0.000)

NOTE.- The dependent variable is log hourly wages in the first job. Factors are constructed from the measurement-invariant cognitive factor and dedicated non-cognitive factors: cognitive skill is estimated from a trimmed age-17 item set with equal loadings across cohorts, while social and diligence skills are dedicated factors based on their corresponding non-cognitive item sets. The factors are standardized in the pooled sample before the cohort split. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in measurement-invariant cognitive skills θ^{cog} , dedicated diligence skills θ^{dil} , and dedicated social skills θ^{soc} , including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 52: Wage returns to cognitive and Big Five skills by cohort: direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.074 (0.067)	0.019 (0.057)	0.205*** (0.061)	0.169*** (0.063)	0.132*** (0.051)	0.151*** (0.038)
Cognitive skills (θ^{cog})	0.093*** (0.032)	0.051* (0.029)	0.084*** (0.031)	0.053 (0.033)	-0.009 (0.026)	0.002 (0.020)
Conscientiousness (θ^{cons})	0.023 (0.029)	0.004 (0.024)	0.003 (0.025)	-0.002 (0.024)	-0.020 (0.026)	-0.007 (0.019)
Extroversion (θ^{extr})	-0.020 (0.028)	-0.019 (0.023)	0.060** (0.024)	0.056*** (0.022)	0.080*** (0.023)	0.075*** (0.015)
Cognitive skills (θ^{cog}) \times Conscientiousness (θ^{cons})	-0.022 (0.030)	-0.011 (0.023)	0.049 (0.032)	0.054** (0.027)	0.072*** (0.025)	0.065*** (0.007)
Cognitive skills (θ^{cog}) \times Extroversion (θ^{extr})	-0.001 (0.031)	-0.007 (0.023)	0.008 (0.026)	0.008 (0.024)	0.009 (0.023)	0.015** (0.006)
Conscientiousness (θ^{cons}) \times Extroversion (θ^{extr})	-0.002 (0.020)	0.000 (0.000)	0.002 (0.014)	0.000 (0.000)	0.004 (0.024)	0.000 (0.000)

NOTE.- The dependent variable is log hourly wages in the first job. Skill factors use the baseline age-17 cognitive factor and replace the baseline diligence and social factors with standardized Big Five conscientiousness and extroversion measures (ENDO_B5C and ENDO_B5E), standardized in the pooled sample before the cohort split. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in cognitive skills θ^{cog} , conscientiousness θ^{cons} , and extroversion θ^{extr} , including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 53: Wage returns to multidimensional skills by cohort (three unobserved types): direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.182*** (0.047)	0.100** (0.047)	0.261*** (0.069)	0.228*** (0.068)	0.079 (0.048)	0.128*** (0.045)
Cognitive skills (θ^{cog})	0.096*** (0.023)	0.042** (0.019)	0.096*** (0.030)	0.069** (0.029)	0.000 (0.023)	0.027 (0.017)
Diligence skills (θ^{dil})	0.078*** (0.024)	0.046** (0.020)	-0.002 (0.028)	-0.012 (0.025)	-0.079*** (0.021)	-0.058*** (0.014)
Social skills (θ^{soc})	0.041* (0.023)	0.035* (0.020)	0.070*** (0.026)	0.074*** (0.025)	0.030 (0.022)	0.038** (0.017)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.017 (0.027)	-0.019 (0.020)	0.059* (0.032)	0.061** (0.028)	0.076*** (0.028)	0.080*** (0.016)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.012 (0.025)	-0.005 (0.020)	0.037 (0.032)	0.036 (0.028)	0.049* (0.028)	0.041*** (0.013)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.021 (0.033)	0.004 (0.028)	-0.098** (0.041)	-0.081** (0.039)	-0.077** (0.031)	-0.085*** (0.022)

NOTE.- The dependent variable is log hourly wages in the first job. This robustness specification uses three unobserved types. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 54: Wage returns to multidimensional skills by cohort in the simplified model: direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	-0.031 (0.058)	-0.017 (0.056)	0.268*** (0.074)	0.259*** (0.075)	0.299*** (0.025)	0.276*** (0.025)
Cognitive skills (θ^{cog})	0.087*** (0.029)	0.082*** (0.029)	0.082** (0.037)	0.083** (0.036)	-0.005 (0.012)	0.000 (0.010)
Diligence skills (θ^{dil})	0.001 (0.028)	0.012 (0.026)	-0.002 (0.031)	-0.006 (0.031)	-0.003 (0.011)	-0.018* (0.010)
Social skills (θ^{soc})	-0.008 (0.026)	0.003 (0.025)	0.071** (0.028)	0.072** (0.028)	0.080*** (0.014)	0.069*** (0.013)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.025 (0.022)	-0.025 (0.021)	0.081*** (0.029)	0.077*** (0.029)	0.107*** (0.013)	0.102*** (0.011)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.022 (0.025)	-0.023 (0.023)	0.032 (0.033)	0.031 (0.032)	0.053*** (0.015)	0.054*** (0.011)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.063*** (0.024)	-0.065*** (0.024)	0.005 (0.033)	0.003 (0.032)	0.068*** (0.015)	0.069*** (0.012)

NOTE.- The dependent variable is log hourly wages in the first job. The simplified model has seven steps: upper-secondary recommendation, upper-secondary enrollment, cognitive skills, diligence skills, social skills, higher-education completion, and starting wages. It uses the same baseline age-17 cognitive, diligence, and social factors as the main specification, constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Direct returns hold higher-education completion fixed, while total returns allow higher-education completion to adjust. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 55: Wage returns to multidimensional skills by cohort: direct and total effects of a one standard deviation (σ) increase

	M (1987-1995)		Trimmed Z (1996-1998)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.157*** (0.049)	0.061 (0.049)	0.293*** (0.078)	0.279*** (0.076)	0.135*** (0.046)	0.218*** (0.038)
Cognitive skills (θ^{cog})	0.107*** (0.022)	0.045** (0.022)	0.105** (0.042)	0.098** (0.042)	-0.002 (0.033)	0.053** (0.025)
Diligence skills (θ^{dil})	0.056** (0.024)	0.028 (0.019)	0.043 (0.033)	0.025 (0.027)	-0.013 (0.027)	-0.003 (0.015)
Social skills (θ^{soc})	0.030 (0.023)	0.022 (0.018)	0.089** (0.037)	0.087*** (0.028)	0.059* (0.031)	0.065*** (0.017)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.026 (0.027)	-0.030 (0.020)	0.052 (0.042)	0.063* (0.033)	0.078** (0.032)	0.093*** (0.013)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.012 (0.025)	-0.004 (0.019)	0.005 (0.038)	0.007 (0.029)	0.017 (0.032)	0.011 (0.013)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.051 (0.038)	-0.017 (0.030)	-0.064 (0.058)	-0.073 (0.052)	-0.013 (0.045)	-0.056* (0.032)

NOTE.- The dependent variable is log hourly wages in the first job. Cohort M uses the benchmark sample, while trimmed Cohort Z includes individuals born between 1996 and 1998, excluding younger birth cohorts whose tertiary-degree outcomes may be right-censored by the 2020 observation window. The table uses the baseline age-17 cognitive, diligence, and social factors, constructed in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 56: Wage returns to multidimensional skills by cohort, excluding individuals at the threshold

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.137** (0.054)	0.046 (0.055)	0.262*** (0.081)	0.255*** (0.078)	0.125** (0.049)	0.209*** (0.038)
Cognitive skills (θ^{cog})	0.105*** (0.027)	0.056** (0.025)	0.095** (0.038)	0.068* (0.036)	-0.010 (0.024)	0.012 (0.016)
Diligence skills (θ^{dil})	0.049* (0.026)	0.017 (0.021)	0.006 (0.029)	0.009 (0.026)	-0.043** (0.022)	-0.008 (0.012)
Social skills (θ^{soc})	0.045* (0.025)	0.042** (0.020)	0.097*** (0.034)	0.107*** (0.030)	0.052** (0.024)	0.064*** (0.017)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	-0.039 (0.029)	-0.048** (0.023)	0.042 (0.034)	0.048 (0.030)	0.082*** (0.027)	0.096*** (0.012)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.020 (0.028)	-0.021 (0.022)	0.023 (0.031)	0.023 (0.029)	0.044* (0.025)	0.044*** (0.012)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.058 (0.043)	-0.039 (0.034)	-0.089* (0.052)	-0.059 (0.047)	-0.031 (0.033)	-0.020 (0.021)

NOTE.- The dependent variable is log hourly wages in the first job. In this table, individuals born in 1994, 1995 and 1996, at the threshold of the cohort definitions, are excluded. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 57: Wage returns to multidimensional skills by cohort using present value of earnings

	M (1987-1995)		Z (1996-2003)		Changes across cohorts	
	Total	Direct	Total	Direct	Total	Direct
Aggregate skills	0.081 (0.070)	0.109 (0.085)	0.002 (0.102)	0.064 (0.105)	-0.079 (0.063)	-0.046 (0.045)
Cognitive skills (θ^{cog})	0.073** (0.035)	0.092** (0.043)	0.058 (0.050)	0.109* (0.055)	-0.015 (0.029)	0.017 (0.021)
Diligence skills (θ^{dil})	0.041 (0.034)	0.048 (0.033)	-0.086** (0.036)	-0.085** (0.034)	-0.126*** (0.032)	-0.133*** (0.022)
Social skills (θ^{soc})	-0.018 (0.033)	-0.008 (0.035)	-0.014 (0.044)	-0.003 (0.040)	0.004 (0.031)	0.005 (0.024)
Cognitive skills (θ^{cog}) \times Diligence skills (θ^{dil})	0.032 (0.032)	0.022 (0.031)	0.023 (0.045)	0.017 (0.039)	-0.009 (0.032)	-0.005 (0.019)
Cognitive skills (θ^{cog}) \times Social skills (θ^{soc})	-0.046 (0.032)	-0.045 (0.032)	0.025 (0.041)	0.026 (0.036)	0.070** (0.027)	0.070*** (0.015)
Diligence skills (θ^{dil}) \times Social skills (θ^{soc})	-0.033 (0.055)	-0.044 (0.058)	-0.148** (0.066)	-0.194*** (0.067)	-0.115*** (0.034)	-0.151*** (0.028)

NOTE.- The dependent variable is log present value of earnings. Skill factors are constructed from age-17 SOEP measures in the pooled sample before the cohort split: the cognitive factor combines grades, advanced-course indicators, parental-involvement indicators, and cognitive-test items, while the diligence and social factors are recovered from a two-factor latent model of non-cognitive/personality, preference, emotional-state, and activity measures. Coefficients represent the percentage change in wages associated with a one standard deviation (σ) increase in skills. Cohort M includes individuals born between 1987 and 1995, and Cohort Z includes individuals born between 1996 and 2003. “Aggregate skills” refers to the combined return to a one SD increase in all three skill dimensions (cognitive θ^{cog} , diligence θ^{dil} , social θ^{soc}), including complementarities. “Direct” returns hold school-to-work transition choices fixed, while “Total” returns also include the effects of skills on endogenous choices. Interaction terms capture complementarities between skills. “Changes across cohorts” are differences in estimated coefficients between cohorts. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table 58: Effects of higher tertiary education on multidimensional skills development (raw)

	(1)	(2)	(3)
	Cognitive skills	Social skills	Diligence skills
Higher tertiary education enrollment	0.234* (0.079)	0.001 (0.045)	0.091 (0.045)
Higher tertiary education diploma	0.037 (0.105)	0.179*** (0.043)	0.241*** (0.058)
Exogenous variables	Yes	Yes	Yes
Skills at age 17	Yes	Yes	Yes
<i>N</i>	738	2489	2489

NOTE.— This table includes the impact of higher education on subsequent skill development over a subsample of individuals. This includes the set of exogenous variables and the skills as measured at age 17.

Table 59: Effects of higher tertiary education on multidimensional skills development

	(1)	(2)	(3)
	Cognitive skills	Social skills	Diligence skills
Higher tertiary education enrollment	0.047 (0.065)	-0.083 (0.043)	-0.086 (0.047)
Higher tertiary education diploma	-0.095 (0.071)	0.040 (0.033)	-0.085 (0.044)
Exogenous variables	Yes	Yes	Yes
Skills at age 17	Yes	Yes	Yes
<i>N</i>	738	2492	2492

NOTE.— This table includes the impact of higher education on subsequent skill development over a subsample of individuals. This includes the set of exogenous variables and the skills as measured at age 17. This includes the effect on the ranking differences based between skills at age 17 and skills at later ages.

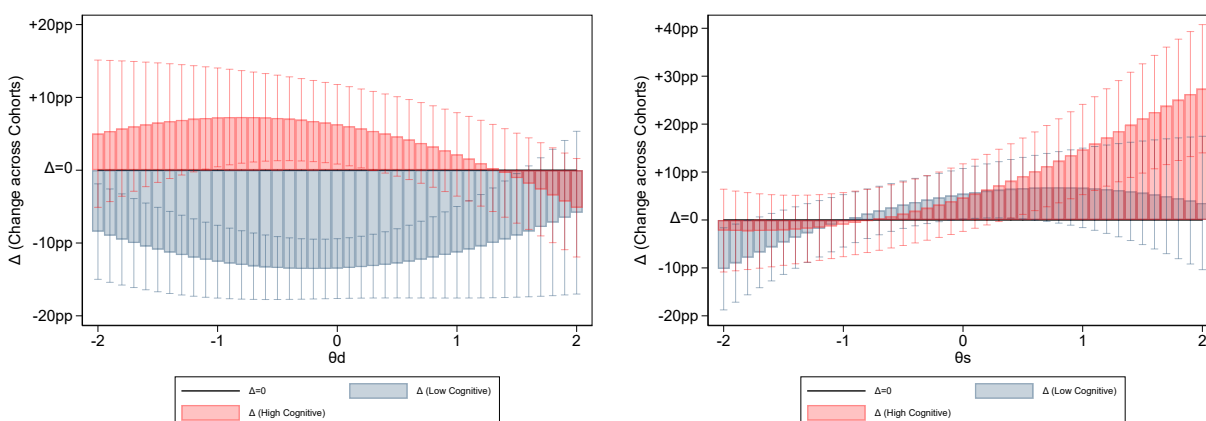
Table 60: Effects of one standard deviation increase in multidimensional skills on occupational sorting: 75th-percentile task threshold

	Occupational task content sorting:		
	Social task	Routine task	Cognitive task
Cognitive skills (θ^{cog})	0.008* (0.004)	0.004 (0.004)	0.043*** (0.005)
Diligence skills (θ^{dil})	0.011*** (0.004)	0.013*** (0.004)	0.049*** (0.005)
Social skills (θ^{soc})	0.014*** (0.004)	0.007** (0.003)	0.043*** (0.005)

NOTE.—Each occupation is classified with a binary outcome, where 1 defines an occupation with task content above the 75th percentile in either social, routine, or nonroutine analytical (cognitive) task. The model is re-estimated using these three binary outcomes in place of starting wages. Entries report changes in the probability of sorting into the corresponding task-intensive occupation, associated with a one standard deviation (σ) increase in skills. Standard errors across simulation draws are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

C.2: Distributional treatment effects The baseline results report average changes in returns to one standard deviation increases in each skill. To examine whether these changes differ across the multidimensional skill distribution, I estimate a more flexible wage specification that includes a third-order polynomial in cognitive, diligence, and social skills, together with their complementarities.⁴⁵ I then compute model-implied returns to each skill at different points of the skill bundle distribution. This exercise follows the logic of distributional treatment effects in Aakvik et al. (2005): heterogeneity in returns is recovered from the parametric structure of the wage equation and the finite-type model of unobserved heterogeneity.

Figure 12: Changes in returns along distribution of diligence (θ^{dil}) and social (θ^{soc}) skills for low ($\theta^{cog} < 0$) and high ($\theta^{cog} > 0$) cognitive individuals



NOTE.— This graph reports the change in total returns to skills (in percentage points) across cohorts, estimated at each point of the skill distribution. To evaluate the marginal returns given the polynomial specification, I hold the remaining non-cognitive skill constant at zero (its mean). The plotted lines represent the average partial effect of the cohort change, computed by averaging over the empirical distribution of observed characteristics for individuals with high ($\theta^{cog} > 0$) and low ($\theta^{cog} < 0$) cognitive skills.

Figure 12 summarises these distributional effects separately for individuals with low and high cognitive skills. The left panel reports changes in returns to diligence skills across the diligence distribution, while the right panel reports changes in returns to social skills across the social-skill distribution. In each case, the figure holds the other skill dimensions fixed and plots the change in returns across cohorts relative to no change, $\Delta = 0$.

The decline in returns to diligence is concentrated among individuals with low cognitive skills. For high-cognitive individuals, changes in returns to diligence are generally not significantly negative and become positive in parts of the distribution. By contrast, low-cognitive individuals expe-

⁴⁵The specification includes third-order terms in multidimensional skills and their interactions.

rience large negative changes in returns to diligence across most of the diligence distribution. For social skills, the increase in returns is less sharply split by cognitive skills, but the gains are largest among high-cognitive individuals with above-average social skills.

These distributional patterns sharpen the interpretation of the average results. The decline in returns to diligence is not uniform across workers; it is concentrated among low-cognitive individuals, especially those whose skill bundle is more exposed to routine-task work. This is consistent with the occupational-sorting evidence in Section 6.2, which shows that high-diligence workers are more likely to sort into routine-intensive occupations. In the context of deroutinisation, this sorting pattern is consistent with diligence becoming less rewarded across cohorts.