Swiss Leading House
Economics of Education • Firm Behaviour • Training Policies

Working Paper No. 212

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UNIVERSITÄT BERN

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The Swiss Leading House on Economics of Education, Firm Behavior and Training Policies is a Research Program of the Swiss State Secretariat for Education, Research, and Innovation (SERI).

www.economics-of-education.ch

Math Skills, Selection in Training Firms, and Post-Training Wages[*]

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February 2023

Abstract

This paper analyzes the association between an individual's mathematical skills in ninth grade, the subsequent selection process in firm-based apprenticeship training, and post-training skilled worker wages. Using data from the National Educational Panel Study and the Institute for Employment Research, we show that math skills are associated with training placements in larger and higher-paying firms, as well as higher subsequent skilled worker wages. Furthermore, we apply instrumental variables regression to account for measurement error in standardized math test scores. We find that a one-standard deviation increase in math skills is initially associated with a 36% increase in initial post-training earnings, reducing to 10% after five years. Our results suggest that math skills help school leavers find an apprenticeship in firms in which they have a comparative advantage, thereby increasing allocation efficiency. Moreover, when we control for observable cognitive and non-cognitive skills, we find that female school-leavers sort into lower-paying training firms. This selection accounts for a significant portion of the gender wage gap observed later among women who continue their careers as skilled workers within their training firms.

Keywords: Math skills, Cognitive skills, Non-cognitive skills, Apprenticeship training, Post-training earnings

JEL Codes: I26, J23, J24, J31, M51, M53

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[*] We are grateful for the support provided by the Research Data Centre (FDZ) at the Federal Employment Agency regarding data access and analysis for this project. This study uses the National Educational Panel Study (NEPS), Starting Cohort 4 (SC4) survey data linked to administrative data of the IAB (NEPS-SC4-ADIAB) – Version 7521 v1, DOI: 10.5164/IAB.NEPS-SC4-ADIAB7521.de.en.v1. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. We are also grateful for comments provided by seminar participants at LMU Munich, University of Zurich and participants at the LESE Conference 2024 in Lisbon and the 8th International NEPS Conference in Bamberg.

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1. Introduction

The transition from school to work is a crucial phase in a person's life, as it can determine the direction and success of their future career. This transition requires a complex process of matching skills, preferences, and opportunities, as well as adjusting to new roles and expectations. The importance of cognitive skills in the hiring process was recently documented by Arellano-Bover (2021), showing a positive association between cognitive skills and the size of an individual's first employer. As training and development opportunities and management differ strongly between firms, the quality of the first employer and the associated accumulation of cognitive skills are of crucial importance for an individual's future career (Altonji & Pierret, 2001; Arellano-Bover, 2024). For individuals with low levels of cognitive skills, the school-to-work transition poses a challenge in many countries, which is reflected in high levels of youth unemployment, particularly in countries without a vocational training system (Ryan, 2001). Moreover, as Deming and Noray (2020) pointed out, there is still little direct knowledge that links the specific skills that individuals acquire during school to employers' skill demands. A better understanding of the hiring process for an individual's transition from school to work may also shed more light on our understanding of the still persistent gender pay gap. The vast empirical literature identified occupational choice among other factors as a key determinant (Blau & Kahn, 2017; Goldin, 2014; Lazear & Rosen, 1990) but also revealed that women are more likely to sort in low-wage firms (Card et al., 2016).

In this paper, we focus on how mathematical competency and a variety of other cognitive and non-cognitive skills are associated with the selection process in training firms (i.e., the initial transition from school to apprenticeship training) and the subsequent earnings trajectory (i.e., the second transition from apprenticeship training in the labor market), offering key insights into the interplay of educational skills and career success. The substantial impact of cognitive abilities on labor market outcomes has been recognized for a long time (Chetty et al., 2011; Hanushek & Woessmann, 2008; Hanushek et al., 2015; Leuven et al., 2004; Murnane et al., 1995; Palczyńska, 2021). Mathematics has been identified as a crucial determinant of labor market outcomes (Altonji, 1995; Falch et al., 2014; Joensen & Nielson, 2009; Leveine & Zimmerman, 1995; Rose & Betts, 2004). However, estimating the effects of cognitive abilities on labor market success is challenging as they may correlate with other, often unobserved, non-cognitive skills (Almlund et al., 2011; Borghans et al., 2008; Bowles et al., 2001; Heckman & Kautz, 2012; Lin et al., 2018), which are also positively associated with various labor market outcomes (Goldsmith et al., 1997; Kautz et al., 2014; Palczyńska, 2021).

Moreover, potentially serious selection issues arise to the extent that individuals with high levels of cognitive (and non-cognitive) skills sort into occupations and firms that offer better employment conditions, including higher earnings and possibly better future training and development opportunities. In markets with incomplete information, firms find it beneficial to screen applicants based on observable variables that correlate significantly with subsequent performance in the workplace, such as grades from compulsory schooling. Thus, it becomes empirically challenging to distinguish to what extent an observed positive association between math grades and post-training wages is due to the signaling value of math skills, or the math skills themselves, essentially posing the same challenge as when it comes to identifying the rate of return to education (Aryal et al. 2022).

For our analysis, we exploit unique data from the German National Educational Panel Study (NEPS), which includes information on math grades, which are observable to potential employers, as well as standardized scores from math competency tests that are not observable to potential employers. Moreover, we incorporate a range of additional cognitive skills, including reading literacy, reasoning, and perceptual speed. We also have information on several non-cognitive skills, such as prosocial behavior and personality traits, including measures of conscientiousness, openness, extraversion, agreeableness, and neuroticism. Finally, we can link all of our information about an individual's cognitive and non-cognitive skills to administrative information from the Institute for Employment Research (IAB), which includes data on individual earnings, as well as important firm characteristics, including the average wage paid in the firm, the size of the firm, as well as unobserved factors related to a firm's overall wage premium that could be extracted based on the linked employer-employee data structure using the AKM model (Abowd et al., 1999). Our data consists of a sample of German pupils in secondary education who were in ninth grade in 2011 when information about cognitive and non-cognitive skills was surveyed. In addition, we can track these individuals throughout their vocational training and subsequently when they enter the labor market as skilled workers. For a large fraction of our sample, we can observe skilled worker wages for up to five years after graduating from vocational training.

Our primary objective is to analyze the association of math skills with two key outcomes: i) the selection of school-leavers into training firms and ii) skilled worker earnings after having acquired a vocational qualification. First, regarding the selection of apprentices in training firms, we focus on four indicators that provide meaningful information about the quality of the first employer: firm size, the average daily full-time wage in the firm, the percentile AKM rank of the firm, and the average daily apprentice wage in the firm.[1] Second, we analyze the association between math skills and post-training wages of apprenticeship graduates in the first five years in the labor market. Furthermore, we uncover gender differences in both the hiring process and the post-training skilled worker wages. To account for potential measurement error in our mathematical skill variable that can lead to attenuation bias, we apply instrumental variables regression techniques. Our final objective is to identify the gender wage gap in an early career stage of skilled workers in Germany.

We find that math grades in ninth grade are important for individuals to find an apprenticeship position in firms that pay higher wages, are larger in size, and higher in the AKM rank distribution, and offer higher apprentice pay. Thus, math grades of school-leavers are associated with the quality of their training firm. Moreover, we find that math grades are relatively more important for male applicants than for female applicants. On the contrary, reading skills are more important for female applicants. Furthermore, we find substantial gender differences in the sorting of school leavers in training firms, as women are more likely to start their training in smaller firms, firms that offer lower pay, and are lower in the distribution of the AKM effects. However, we can also document that most of these differences are due to occupational choice, as the significance of the gender gap disappears when controlling for the occupational field. Nonetheless, deficiencies in cognitive and non-cognitive skills can impact the chance to start an apprenticeship in a high-paying occupation or firm, which in turn affects future earnings. Consequently, the observed disparities in math skills between female and male students might explain why female school leavers often enter training occupations that are associated with lower pay both as an apprentice but also after having obtained a vocational qualification. Finally, by employing an instrumental variables regression approach, we mitigate the attenuation bias due to potential measurement error, uncovering a much more substantial link between mathematical competency and subsequent wage development compared to OLS regression. These findings suggest that researchers should be aware that standard regression techniques may severely underestimate the association of skills that are measured by means of a standardized test with any dependent variable of interest. Our analysis of the gender wage gap reveals that its origin is at the very beginning of women's careers. We can show that even when controlling for cognitive and non-cognitive skills, a substantial gender wage gap exists already in the first year in the skilled labor market. In line with much of the empirical literature, we find that women sort into lower-paying occupations on average. However, even when controlling for the occupational field, our results show that a substantial part of the remaining gender pay gap can be

[1] Arellano-Bover (2024) uses firm size as a proxy for first-employer quality.

explained by AKM effects of the current employer, which is in line with Card et al. (2016) and Di Addario et al. (2023).

The remainder of the paper is structured as follows. Section 2 discussed the relevant literature, including human capital and signaling theory, as well as the relevant empirical literature regarding the selection of trainees in training firms, training completion, and the labor market returns to cognitive and non-cognitive skills. Section 3 introduces the data sets and provides descriptive statistics. In section 4 we outline our estimation strategy. The results are presented in Section 5. In Section 6 we discuss our findings, and Section 7 concludes.

2. Relevant literature

According to human capital theory (Becker 1962; Mincer 1989), workers vary in productivity due to their human capital endowments and investments, which they can increase by acquiring skills and competencies. Individuals have incentives to finance human capital investments in competitive markets, as an increase in marginal productivity is associated with an equal increase in the marginal wage. However, in imperfect markets, training externalities arise as individuals are unable to capture the full extent of the increase in marginal productivity that is related to an investment in human capital. Instead, the monopsony power of the employer enables them to capture part of the return, potentially incentivizing the provision and financing of human capital investments within the workplace (Acemoglu & Pischke 1999). However, in markets with important information asymmetries regarding the expected productivity of job applicants, individuals can acquire a higher education level to signal their productivity to employers, thereby avoiding being paid a wage that is below their value marginal product until employers learn about their true productivity (Spence 1973; Aryal et al. 2022). In our paper, however, we do not focus on the returns to schooling but instead on the returns to cognitive skills, with a particular focus on math competencies, which are acquired during compulsory schooling at the secondary level.

The development of competencies is relevant for both individual success and a functioning democratic society (Weinert et al., 2011). In our paper we focus on domain-specific competencies, particularly math and reading skills, which are developed in schools.[2] However, as individuals progress to later stages such as job training and tertiary education, these competencies become cross-curricular basic competencies. In other words, they become fundamental skills that are

[2] Domain-specific competencies differ from two other types of cognitive abilities. The first type includes general cognitive capacities (such as IQ) that are not specific to any particular context, such as working memory capacity or fluid intelligence. The second type refers to specialized knowledge structures and procedural skills that are specific to a particular content area (Artelt et al., 2013).

applicable across various subjects and areas of study (Weinert et al., 2011). However, despite an increasing proportion of well-educated individuals in OECD countries, many still lack basic numeracy skills, leading to negative impacts on their earning potential and employment opportunities (Cherry & Vignoles, 2020; Hanushek et al. 2015). Mathematical literacy is indispensable for various professions and plays a vital role in informed decision-making, particularly in personal finance. A theoretical framework based on the National Council of Teachers of Mathematics (NCTM) and OECD's PISA frameworks has been developed for all age groups in the National Educational Panel Study (NEPS) (Weinert et al., 2011, p. 77). The NEPS selected the competencies for their assessments based on several intended characteristics. These competencies were expected to provide relevant results for monitoring and optimizing educational processes, be connected to national and international studies, and follow a comprehensive taxonomy. Additionally, the competencies needed to be convertible into tests and instruments, facilitate measurement of change and developmental progress, and provide information on developmental trajectories and underlying processes. The NEPS identified several competencies for assessment, which are divided into various categories. These categories include domain-general cognitive functions (nonverbal reasoning and information-processing speed), domain-specific cognitive competencies (e.g. German-language competencies, mathematical competence, and scientific literacy), and meta-competencies and social competencies (procedural and declarative metacognition, self-regulation, and ICT literacy), as discussed in Artelt et al. (2013).[3]

The evaluation of skill enhancement programs should not only consider cognitive competencies but also broaden the perspective to include meta-competencies and non-cognitive skills domains (Weinert et al., 2011). The predictive power of achievement test scores on later life success is limited. Specifically, adolescent achievement test scores can only explain up to 17% of the variance in later life earnings. This inadequacy stems from the narrow scope of achievement tests, which do not encompass essential non-cognitive skills such as perseverance, conscientiousness, trust, self-

[3] The developmental changes in domain-general abilities are context-free and culture-fair. These abilities are referred to as cognitive mechanics and they form the basis of intelligent thinking and action. On the other hand, domain-specific competencies like reading, mathematical, and scientific literacy are part of cognitive pragmatics, which are declarative and procedural knowledge and skills acquired over the life course. Both cognitive mechanics and cognitive pragmatics are subject to typical age-related changes across the lifespan and are influenced by different determinants. The NEPS focuses specifically on the acquisition of education-dependent, domain-specific competencies, but it is also important to assess cognitive mechanics to understand cognitive performance (Weinert et al., 2011). Two indicators to assess cognitive mechanics, namely figural reasoning tasks and tasks assessing perceptual speed are more language-independent and culture-fair in the NEPS that we use in our analysis.

control, self-esteem, resilience, empathy, openness, humility, tolerance, and social effectiveness. Despite the critical importance of these skills in societal, educational, and labor market settings, they have been overlooked for a long time. Psychologists and economists have developed reliable measures of non-cognitive skills and demonstrated their capacity to predict significant life outcomes (Heckman & Kautz, 2012). It is noteworthy that both cognitive and non-cognitive skills are modifiable and evolve over time and instruction, with non-cognitive skills exhibiting a greater response to later-stage interventions relative to cognitive skills (Kautz et al., 2014). Non-cognitive skills can be as influential as cognitive skills in predicting many outcomes, if not more so (Kautz et al., 2014).Our research incorporates all aspects of the Big Five personality traits - conscientiousness, openness, agreeableness, neuroticism, and extraversion. Additionally, we include prosocial behavior as another non-cognitive indicator and ICT (information and communication technologies) as an indicator of metacognition.

2.1 Relevant empirical literature

In this subsection we provide a brief overview of relevant empirical studies on how cognitive and non-cognitive skills are related to the selection into training and subsequent labor market outcomes.

The role of cognitive and non-cognitive skills in the hiring process

Cognitive and non-cognitive skills are paramount in being selected for an interview and getting hired. In exploring how cognitive and non-cognitive skills associate with the hiring of trainees in the labor market, several empirical studies provide valuable insights. For Germany, Protsch and Solga (2015) conducted a field experiment to analyze who employers evaluate school grades and behavioral evaluations during the initial hiring stages, underscoring the significance of both cognitive and non-cognitive skills in these decisions. Subsequently, Piopiunik et al. (2020) conducted a vignette experiment among German HR managers and demonstrate that overall school GPA, alongside IT skills, English language proficiency, and social skills (such as volunteering) significantly improve the probability of receiving a job interview invitation. However, the insights from vignette experiments primarily illuminate the initial stages of the recruitment process without shedding light on the subsequent phases of job interviews and hiring decisions. For Switzerland, Fossati et al. (2020) analyzed the hiring of Swiss apprentices by examining resumes. Their findings indicate that employers prioritize direct signals such as educational credentials and aptitude test scores, but also consider socioeconomic status indicators, especially in ambiguous situations, which can lead to potential discrimination against lower SES candidates.

Koedel and Tyhurst (2012) broaden the scope beyond trainees to explore the labor market at large. Their field experiment, involving fictitious resumes in various job categories, highlights the distinct value of math skills, especially in enhancing callback rates for sales roles among higher-educated individuals. This nuanced understanding of how specific cognitive skills are valued in different job sectors adds depth to the conversation. Similarly, Baert and Verhaest (2021) analyze the Belgian job market, examining how CV characteristics like degree class and extracurricular activities impact initial hiring outcomes. Their findings suggest that these characteristics are perceived as signals for different types of skills and are crucial to distinguishing candidates in the competitive job market.

Furthermore, Pinto and Ramalheira's (2017) research on the perceived employability of business graduates in Portugal provides an insightful perspective on the interplay between academic performance and extracurricular activities. Their study indicates that high academic achievement, combined with active participation in extracurricular activities, improves the perceptions of employability, offering a comprehensive view of the multifaceted dynamics in the assessment of employability. Collectively, these studies offer a cohesive narrative on how various skills and qualifications are valued in the hiring process of trainees and their influence on labor market outcomes, highlighting the complexity and multifactorial nature of these processes.

Labor market effects of cognitive and non-cognitive skills

Several empirical studies find a strong positive correlation between cognitive skills and labor market outcomes. Using data from the Programme for the International Assessment of Adult Competencies (PIAAC), Hanushek et al. (2015) report that a one-standard-deviation increase in numeracy skills was associated with an 18% wage increase among prime-age workers, though this effect varied from 12% to 28% across countries. However, Hanushek et al. (2017) point out that the wage premium for individuals with higher literacy and numeracy skills varies between countries and reflects the relative demand for and supply of such skills (Hanushek et al., 2015, 2017). Besides using a standardized measure of numeracy skills, as available in the PIAAC data, several studies use information based on the Armed Forces Qualification Test (AFQT) as a measure of cognitive performance, and consistently demonstrate its significant impact on various labor market outcomes. Cognitive performance at the end of secondary schooling, as measured by AFQT scores, is positively associated with labor market success throughout one's career. Lin et al. (2018) found that cognitive skills, as measured by AFQT, exhibit increasing returns with age, influencing annual income, earnings, wages, and annual hours worked. Additionally, disparities in cognitive skills, assessed by AFQT, contribute significantly to wage gaps, particularly between black and white individuals (Neal & Johnson, 1996). Salkever (1995) focused on the relationship between AFQT scores and annual earnings, revealing that even a one-point difference in AFQT scores is associated with a substantial increase in earnings, independent of educational attainment. Related to the uncertainty of a new hire's productivity, Altonji and Pierret (2001) investigated statistical discrimination in the labor market, focusing on how firms' perceptions of worker productivity evolve as they gather more information. They demonstrated that when firms initially rely on easily observable characteristics such as education in their hiring and wage decisions, these observable factors play a more substantial role in determining wages. However, as firms acquire additional information about the workforce, the significance of these easily observable attributes diminishes, while harder-to-observe correlates of productivity, such as the Armed Forces Qualification Test (AFQT) scores, become more influential. Moreover, Grosse & Zhou (2021) found a positive link between childhood cognitive ability and adult economic productivity. They suggest that interventions to protect cognitive function could result in economic gains. The study revealed that each IQ point difference equates to a 1.4% difference in market productivity in the U.S., or USD 10,600–13,100 over a lifetime. Murnane et al. (2000), using data from the 1980s and 1990s, found that cognitive skills modestly affect earnings, with a standard deviation increase in test performance boosting male earnings by 15% and female earnings by 10%. They also found mixed evidence on whether college benefits students with strong cognitive skills. Deke and Haimson (2006) examined the impact of academic and non-academic skills on postsecondary outcomes using NLSY data. While the results show that math skills are crucial, non-academic competencies like work habits, teamwork, leadership, and locus of control also significantly affect earnings. Arcidiacono et al. (2010) highlighted how the labor market rapidly discerns the abilities of college graduates, as reflected in their wages, because of the strong correlation between SAT scores that are observable by employers and the (unobservable) AFQT scores. Conversely, high school graduates cannot signal their competencies to employers, and for that reasons their abilities are gradually revealed over time but eventually the labor market rewards higher cognitive skills with higher wages. Aryal et al. (2022) also provide evidence of the signaling value in the initial years on the labor market, until employers learn the about the true productivity of their employees.

Furthermore, the literature on the impact of mathematics education on labor market outcomes and educational trajectories highlights significant findings from studies in Denmark and Norway. Joensen and Nielsen (2009) exploit a Danish high school pilot scheme that provides compelling evidence for the causal effect of advanced math education on earnings and labor market participation. Their research shows that students who opted for advanced math courses earned approximately 30% more than their peers, suggesting that higher-level math qualifications not only enhance earnings but also lower unemployment rates, thus improving overall labor market participation and stability. Complementarily, Falch et al. (2014) demonstrate the tangible effects of mathematical training on educational outcomes in the context of the Norwegian educational system. In their unique experimental setup, 16-year-old students were randomly assigned to either a mathematics or a language high-stakes exit exam. The study found that even a short period of intensive preparation in mathematics significantly lowered high school dropout rates and increased enrollment in higher education, especially in science and technology fields, with a more pronounced effect observed among male students. Together, these studies underscore the pivotal role of mathematics in shaping both academic and professional futures, emphasizing its value in educational systems and labor markets.

Using a different approach to measuring cognitive skills, Grisberger et al. (2022) analyze Swiss employees with a vocational qualification, focusing on the impact of different skills, but measured at the level of the occupation in which an individual received the vocational qualification, and not at the level of the individual itself. They find that having been trained in occupations where interpersonal, cognitive, and manual skills were part of the training curriculum was positively associated with subsequent earnings in the context of the Swiss labor market.

Our paper makes two substantial contributions to this literature. First, we are to the best of our knowledge the first to identify the importance of cognitive and non-cognitive skills in the matching process of apprenticeship applicants and training firms, as the literature thus far was limited to analyzing the effects on the call-back probability when sending out fictitious resumes or to vignette studies that inquired about hiring probabilities in hypothetical setting. Moreover, we have detailed information not only in the individual but also in the characteristics of the training firm. Second, we can identify the returns to a variety of cognitive and non-cognitive skills in the first years after having completed apprenticeship training and relate these findings to the initial selection of apprentices in the training firm.

3. Data and descriptive statistics

In this section, we first provide information about the underlying data for our analysis, and subsequently provide descriptive statistics.

3.1 Data

Our analysis is based on the NEPS-ADIAB data, a collaborative initiative between the Institute for Employment Research (IAB) and the Leibniz Institute for Educational Trajectories in Germany. The data set combines survey data from the National Educational Panel Study (NEPS) with administrative data from the IAB through a record linkage procedure, providing individual-level information (Bachbauer et al. 2022). NEPS data covers various domains, such as educational pathways, competencies, attitudes, and learning environments. Concurrently, the administrative data of the IAB comprises detailed employment histories dating back to 1975 and extensive insights into establishments. To capture and analyze educational transitions over time, a multicohort sequence design within the National Educational Panel Study (NEPS) during the period 2009 to 2012 was employed. This study was designed with six initial cohorts, ranging from newborns to adults, and included over 70,000 respondents at the beginning of the panel (Bachbauer et al., 2022). We specifically focused on the ninth graders' cohort (SC4), which delved into the educational trajectories of students beyond the ninth grade, tracing their progression into upper secondary education, vocational training, higher education, and the labor market. To accommodate the high mobility characteristic of the individuals in this age group, the cohort began with a substantial initial sample. The panel design was densely structured and involved context individuals, including parents, educators, and teachers. The data portfolio resulting from this effort included scientific use files with data spanning 8 to 15 survey waves. Our study specifically incorporates students from the ninth graders' cohort (SC4) who embarked on dual apprenticeships and commenced their training within a firm after completing the ninth or tenth grade. This subset of students is notable for their early entry into the labor market, facilitating the tracking of their earnings upon completion of training and achieving full-time employment (Bachbauer et al., 2022). The NEPS data includes several cognitive skills, including mathematical competency, reading competency, and ICT skills. Mathematical competency was evaluated using paper-pencil tests covering four areas of mathematical content and six cognitive components (Neumann et al., 2013). Reading competence was assessed through paper-pencil tests that included five text functions and three comprehension requirements (Gehrer et al., 2013), while the assessment of ICT skills involved paper-based assessments that featured screenshots of standard software applications. These tests measured four key process components: access, management, evaluation, and creation, encompassing both technological and cognitive aspects (Senkbeil, Ihme, & Wittwer, 2013). The NEPS data also include non-cognitive variables, primarily the Big Five personality traits, assessed using the 10-item Big Five Inventory (BFI-10), with additional items designed for the Agreeableness domain. These traits included openness, conscientiousness, extraversion, agreeableness, and neuroticism (Rammstedt & John, 2007). In addition to the Big Five traits, "prosocial behavior" was evaluated using the SDQ scale, focusing on elements such as trying to be nice to other people and considering their feelings as important.

Regarding the selection of individuals into training firms, we focus on four indicators: firm size, average daily wage paid to fulltime employees within the firm, AKM rank of the firm, and average daily apprentice wage in the firm. The size of the firm was classified into different categories, including very small firms (less than 10 employees), small firms (between 10 and 49 employees), medium firms (between 50 and 249 employees), and large firms (more than 250 employees). Second, we have information about the average daily wage of full-time employees within a given establishment, denominated in euros. Additionally, we have information on the firm AKM effect (cf. Abowd et al. 1999), which reflects the establishment fixed effect based on the AKM model over a seven-year period from 2014 to 2021, stratified into 20 quantiles, ensuring a balanced representation across the distribution (Bellmann et al. 2020). Finally, we also have information about average daily apprentice wage in a training firm.

To analyze the wage returns to math skills of individuals after having graduated from apprenticeship training, we focus on the daily wage of the employees, measured in euros. Note that is not possible to calculate hourly wages based on the IAB data, because information about weekly work hours is not available. However, we have information about whether an individual works full-time or part-time. For that reason, our analysis of the wage returns to math skills will only focus on the group of employees that works full-time.

3.2 Descriptive statistics

Table 1 reports the descriptive statistics for the full sample of ninth graders who eventually started an apprenticeship. The average math score is lower for female apprentices, but also has a lower standard deviation. Note that the math competency variable is indicative of the relative standing of apprentices in the full sample of ninth graders. Thus, on average, the math competency of male apprentices is (only) slightly below average of all ninth graders, while it becomes apparent that female apprentices have below-average math competencies. Conversely, there is no gender difference in the average reading competency between male and female apprentices. Note, however, that the reading competency of apprentices is below the average reading competency of all ninth graders, which is expected as the reading competency of pupils who stay in the academic track (i.e., continue their education in the academic high school track) have better reading competencies. Regarding personality traits, females have higher levels of conscientiousness, openness, agreeableness, and neuroticism, while there are no differences in the degree of extroversion, in line with recent results for Poland (Palczynska, 2021). Furthermore, we find no gender differences regarding apprenticeship completion rates.

Table 2 reports descriptive statistics for the sample of individuals who graduate with a dual apprenticeship qualification and are employed afterwards. The average daily wage after employment shows that men earn more, with an average of 84.9 Euros per day, compared to women who earn 78.4 Euros. Moreover, the firm's average daily pay for full-time employees is higher in firms where men work, averaging 111.2 Euros, compared to 105.2 Euros in firms where women are employed.

Table 3 offers a concise yet comprehensive view of occupational segments, highlighting gender distribution, average daily wages, and math scores. Notably, female representation is higher in healthcare and social service occupations and lower in fields like building construction and production technology. Wage disparities are evident, with the service sector and cultural work offering the highest average daily wages (95.02 Euro), in contrast to lower wages in commerce and trade (68.56 Euro). Math scores vary significantly, with the highest averages in IT and natural sciences (0.51 on average) and lower scores in healthcare (-0.43 on average). The data indicates a potential correlation between gender distribution and both wages and math scores, where fields with higher female representation generally have lower math scores and a higher wage dispersion.

Daily wages, segmented by quartiles of 9th-grade math performance and years of employment, reveal a clear trend: higher math performance correlates with higher starting wages, and wages increase across all quartiles with additional years of experience (Table 4). For example, individuals in the lowest math quartile start with an average wage of 76.6 Euros and see an increase to 85.8 Euros over four years, while those in the highest quartile begin at 87.9 Euros and grow to 94.9 Euros in the same period. This pattern of wage development is consistent across all levels of math proficiency.

4. Identification Strategy

As noted by Aryal et al. (2022, p.1698), information revealed at school (i.e., cognitive skills) may affect the matching efficiency of individuals into different occupations and firms, such that the "highest bidder" will be able to recruit those apprentices with the highest skill levels, to the extent that employers are able to assess these skills during the hiring process.[4] For that reason, as a first step, we analyze the association of cognitive and non-cognitive skills in the transition from school to apprenticeship training. We use four different indicators that reflect whether an individual starts an apprenticeship in a high-quality employer in terms of firm size, average wage level but also in terms of the firm's AKM rank, which is typically interpreted as a wage premium that all workers receive in a particular firm independent of their education and experience.

[4] Indeed, many apprentices spend a few days working in the company before being offered an apprenticeship contract (*Probearbeit*), which may increase the employer's ability to assess or identify the corresponding skills of the apprentice.

Thus, we estimate the hiring process h of individual i into apprenticeship training in firm j as follows:

$$h_j = \alpha \mathrm{C}_i + \beta \mathrm{N}_i + \varepsilon_i \tag{1}$$

where h denotes the four different indicators that characterize the training company, $\mathrm{C_i}$ denotes cognitive skills, including math and reading competencies, $\mathrm{N_i}$ denotes non-cognitive skills.

Subsequently, and similarly to Farber and Gibbons (1996) and Altonji and Perret (2001), model the dynamics of the productivity of worker i working in firm j in year t in the labor market as given by

$$y_{ijt} = \alpha e_t + \beta \mathrm{C}_i e_t + \gamma \mathrm{N}_i e_t + \delta \mathrm{F}_j + \eta \mathrm{X} + \lambda_t + \mu_{ijt} \tag{2}$$

where $\mathrm{F_j}$ denotes firm characteristics, including the average daily wage paid to full-time workers, the AKM rank, and firm size, and e_t denotes the experience of individual i in the labor market as a skilled worker, and X includes gender, occupational field, and general intelligence. We also include year dummies λ_t to account for changing labor market conditions that may impact initial skilled worker wages (von Wachter 2020).

Finally, potential measurement error in the variables representing cognitive skills, particularly math competency, may lead to attenuation bias. To mitigate this issue, we employ an instrumental variables (IV) regression approach, as previously suggested in Hanushek et al. (2015). Specifically, we use the final math grade in 9th grade as an instrumental variable for the math competency measured in NEPS. The coefficient in the instrumental variable regression reflects the shared variance in mathematical skills, as indicated by math grades from ninth-grade transcripts and the math competency assessments reported in NEPS. Following Aryal et al. (2022), we estimate the instrumental variables regressions separately for each t to allow for a weaker functional form assumption.[5]

5. Results

In this section we present the regression results that identify the importance of cognitive and non-cognitive skills regarding the sorting of apprentices in training firms. Moreover, we analyze the association between math skills and wage development in graduated apprentices, and we apply instrumental variables regression techniques to account for measurement error. Finally, we

[5] We also estimated OLS regressions separately for each t and obtained similar results as in the specification of Equation (2). For a more concise presentation of the results, we only present OLS results derived from Equation (2).

comment on the observed gender wage gap during the first years of graduated apprentices in the skilled labor market.

5.1 Selection in training firms

We find that the final math grade in ninth grade is positively associated, especially for males, with starting their apprenticeship training in larger firms, firms with a high average wage, a high AKM rank and higher average apprentice wages.[6] The effects are also of economic importance. A one standard deviation increase in math competencies is associated with a 0.44 increase in the AKM rank of the training firm, which corresponds to an increase of $0.44 \times 5 = 2.2$ percentiles in the distribution of the AKM effects.[7] Moreover, a one standard deviation increase in math competency is associated with an individual starting apprenticeship training in a firm with a 3.2% higher average daily wage for full-time workers, and a 2.9% higher average wage for apprentices. However, even though the point estimates are positive, none of the effects are statistically significant for female school-leavers expect for the average daily wage of a full-time employee in the training firm. The corresponding effect size of 2.7% is, however, lower in magnitude compared to males and only marginally significant at the 10% level (Table 5). Conversely, reading competencies matter more for female apprentices, as the effect sizes are higher compared to male apprentices. Female apprentices with above-average reading skills are more likely to start an apprenticeship in better-paying and larger firms, and with a higher average apprentice wage. Moreover, reasoning skills are strongly associated with starting an apprenticeship in better-paying and larger firms for females but not for males. In turn, ICT skills are again more important for males when it comes to starting an apprenticeship in a high-wage or a large firm, but not for females.

We do not find strong evidence for an important role of the Big Five personality traits regarding the selection in apprenticeship training, except for two variables: First, conscientiousness, which is positively associated with the overall wage level in the training firm, but only for male apprentices. The effect size is comparable to that of math competency. Second, again only for male apprentices, we find that neuroticism is negatively associated with the overall wage level and the AKM rank of the training firm.

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[6] We also estimated the same regression models using math competency as the independent variable instead of math grades. The results are qualitatively similar. However, we report math grades because in the selection process, firms can readily observe math grades, as applicants are typically required to provide grade statements in the hiring process.

[7] The variable AKM rank is defined as follows: "This variable contains the position of the establishment effect in the overall distribution of establishment effects for female and male workers in the period 1993 to 1999 in 20 quantiles." (Bellmann et al. 2020, p. 14).

Finally, we find evidence for gender disparity regarding the selection in training firms, as females are generally less likely to start their apprenticeship training in high-paying firms, large firms, or firms with a high AKM rank. Furthermore, women are also more likely to select into firms that offer a lower apprentice wage (Table 6). However, a substantial portion of these differences is driven by the fact that women sort into different training occupations. We find that once we include the occupational field in the regression models, the gender gap closes almost entirely except for apprentice pay, indicating that the skill requirements of training firms vary strongly by the respective training occupations. However, it should be noted that occupational choice in itself depends on an individual's skill set in grade nine, and for that reason we conclude that a substantial gender gap does in fact exist in the transition process from school to apprenticeship training.[8]

In sum, we find that both cognitive and non-cognitive skills are important drivers when it comes to the selection in a particular training company, although based on our results it appears that cognitive skills are more important compared to non-cognitive skills. In the next subsection we turn our focus on whether these skills are not only associated with the selection into apprenticeships, but also have a longer-term correlation with an individual's wage after successfully having completed apprenticeship training.

5.2 Post-training wages

We find that math skills not only matter for the initial selection in training firms but are also associated with skilled worker wages of individuals after having obtained their vocational qualification. Without including any control variables, our results suggest that a one standard deviation increase in math skills is associated with a 4.9% wage increase for males with one year of experience in the labor market (Table 7, Model 1). The effect size subsequently decreases to 2.7% for individuals with five years of labor market experience. For females, the corresponding effect size is initially 7.4% and decreases to 4.1% with five years of labor market experience. When including additional control variables, such as general intelligence, and non-cognitive skills, the effect size of math skill decreases, and its statistical significance decreases as well when running

[8] Including control variables that are outcomes of the independent variables of interest are known as "bad controls" in the literature and should hence not be included in a regression (cf. Angrist and Pischke 2009, section 3.2.3). However, the exercise is still insightful because it provides us with relevant information about the source of the observed gender gap in the regression models where we do not control for the occupational field. However, occupational choice not only depends on financial factors but also depends on (unobserved) preferences, making the assessment regarding the existence of a gender gap in the hiring process a difficult task.

separate regressions by gender. However, it remains statistically significant in the full sample (Table 7, Model 2).[9]

Including control variables for the occupational field slightly decreases the coefficient on math skills (Table 7, Model 3). Furthermore, as recently argued in a series of papers by Arellano-Bover (Arellano-Bover 2021, 2022, 2024) training quality may be superior in larger firms, leading to a spurious correlation between math skills and post-training wages. Indeed, when adding firm size as well as the AKM rank variable as a control, the coefficients on math skills decrease to 1-2% (Table 7, Model 4).[10] However, as we show in Section 5.3 below, the coefficient on math remains statistically significant when accounting for measurement error even when we include controls for firm characteristic.

We also find a significant gender wage gap of 8-10% that is persistent when controlling for the occupational field (Table 7, Models 1-3). However, when accounting for firm characteristics, including the AKM rank, firm size and the average wage of a full-time worker, the gender wage gap decreases to 5.7% (Table 7, Model 4).

While math skills may be merely a signal for high-productive apprentices that facilitates the matching process between apprentices and the training firm, such skills may also prove to be valuable again after training completion for those apprentices who either did not receive an offer to remain with the training firm as a skilled worker, or for those apprentices who decided to quit (e.g., for personal reasons). Therefore, we also separately analyze the association between math skills and skilled worker wages for both movers (i.e., apprentices who leave the training firm after completion of training) and stayers (i.e., apprentices who remain with the training firm as skilled workers after completion of training). However, we find no substantial differences in the association of math competency and the post-training wage between the two groups (Table 8), suggesting that math skills are equally valuable for those who remain in the training firm and for those who decide to quit, or did not receive an offer to stay on as a skilled worker.

However, we find a notable difference in the gender wage gap between the two groups. While women who stay with the training firm on average earn 9.9% less compared to men, the corresponding wage differential is 6.3% and thus significantly lower for women who leave the training firm after completing their apprenticeship training (Table 8, Model 1). The difference in

[9] We also included interaction terms of the other cognitive and non-cognitive skills in the wage regressions but refrain from reporting the coefficients because they were not statistically significant.
[10] Note that we find a statistically significant association of firm size and the AKM rank with the post-training wage in Model 4 of Table 7, as would be expected. Moreover, we include year dummies to control for different labor market conditions which may affect starting wages (Arellano-Bover, 2022).

the gender wage gap between movers and stayers is even more pronounced when we include additional cognitive and non-cognitive skills (Table 8, Model 2). Interestingly, the gender wage gap for stayers decreases 4.6% when we control for firm characteristics, which indicates that women might substantially improve their earnings when switching employers after graduating from apprenticeship training, rather than staying with their initial training firm.[11] In other words, because women are sorted into lower-paying firms in comparison to men (as shown in Table 5), much of the observed gender-wage gap in the first years after having completed can be explained by firm characteristics. They reason why some women remain in low-wage firms after having completed training is beyond the scope of our analysis but may possibly be related to higher monopsony power of training firms over female than over male employees (e.g., due to potentially higher mobility costs of women).

5.3 Using instrumental variables regression to account for measurement error

As pointed out, among others, by Hanushek et al. (2015), skills may contain significant measurement error. To the extent that measurement error is random, instrumental variables regression is helpful to mitigate attenuation bias. We use the final math grade in ninth grade as an instrument for math competency, which is measured in the context of NEPS. We find that the two variables are highly correlated yet independent measures of an individual's math skills. While ninth-grade math grades also contain a significant amount of measurement error, the main source of the measurement error likely can be attributed to the teacher and the exam itself, which should be unrelated to the competency measures in NEPS. Indeed, the high F-statistics associated with the IV across all years confirm the strong correlation between math grades and math skills (Table 9). Our second stage results reveal that the point estimate of the association between math skills and the wage is considerable higher than the OLS estimates, with a gradually diminishing effect in subsequent years. Thus, it appears that our OLS estimates in Table 8 indeed suffer from substantial attenuation bias, as the IV estimates reveal a much higher return to math skills, particularly in the first years on the labor market. A similar picture emerges in the subsample analysis by gender, although the coefficient on math skills is no longer statistically significant and is close to zero for women after four and five years of experience in the labor market (Tables 10, 11). However, it should be noted that the number of individuals with five years of work experience is rather low.

[11] Note that we do not identify an exogenous variation in the decision to remain with the training firm or to switch employer, thus our results are biased to the extent that other unobserved factors beyond the cognitive and non-cognitive skills that we observe are relevant to an individual's post-training mobility and at the same time correlated with future earnings.

6. Discussion

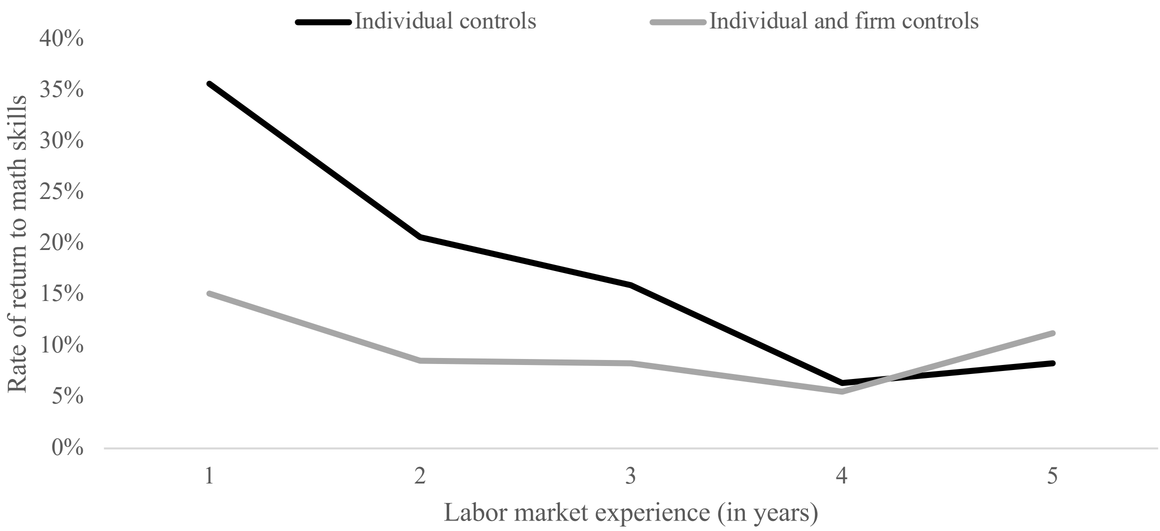
Our analysis focused on the association of cognitive and non-cognitive skills and the selection in training firms in the context of the German dual apprenticeship system, as well as the extent to which these skills are associated with post-training wages. We find evidence for a strong association between cognitive skills (and math skills in particular) in determining selection outcomes of the hiring process, in line with recent findings of Arellano-Bover (2021), who shows based on PIAAC data that cognitive skills (as measured by numeracy skills) are positively associated with being employed at a large firm. Furthermore, we are also able to show that cognitive skills are associated with starting apprenticeship training at a higher-quality training firm. Thus, our results imply that German school-leavers can signal their skills during the hiring process and thereby improve allocation efficiency. This result is in stark contrast to Arcidiacono et al. (2010), who report that US high school graduates are not able to signal their skills, as it takes US employers several years to learn about their true productivity, implying that German employers' belief that math grades, at least to some extent, reveal important information about an individual's math skills, or other productivity-enhancing skills.[12] These findings are in line with the findings of Fossati et al. (2020) and Piopiunik et al. (2020), who emphasize the weight of educational credentials in the first stage of the hiring process in the German and Swiss apprenticeship markets. This is particularly evident for males, where higher math and reading competencies significantly increase the likelihood of selection into better training firms. On the other hand, the study highlights a notable gender disparity, as reading skills are relatively more important for women. Moreover, we find that non-cognitive skills, such as prosocial behavior, but also character traits, do not play a major role in the sorting of apprentices into training firms, nor in predicting subsequent skills worker wages (except for conscientiousness). However, it is important to note that contrary to the literature that conducts vignette studies or correspondence testing studies, which can only identify the effects on the invitation for a job interview (Protsch & Solga, 2015) or hypothetical hiring processes (Fossati et al., 2020; Piopiunik et al., 2020), we observe the outcome of individuals having actually concluded an apprenticeship training contract with a firm.

Our study highlights the significant link of math skills with post-training wage development, although we cannot identify causal effects of math skills in the absence of an experimental or quasi-experimental setting. The results broadly align with Hanushek et al. (2015, 2017), Lin et al. (2018),

[12] Conversely, Arcidiacono et al. (2010) also show that standardize SAT scores help college graduates to signal their skills, such that individuals with higher cognitive skills immediately receive higher wages when they enter the labor market. In our context, German school leavers can signal their math skills by means of the final math grade in their school transcripts.

Joensen and Nielsen (2009), and Falch et al. (2014), highlighting the importance of mathematical skills in the labor market. While Hanushek et al. (2015, 2017) reported that, on average, a one-standard-deviation improvement in numeracy skills is associated with an 18% wage increase among workers in their prime age using cross-sectional data, we find a 30% wage increase during the first year in the labor market for each standard deviation increase in math abilities, which, however, decreases to less than 10% after four years of experience. Thus, our findings indicate that it is important to analyze the returns to skills in a dynamic setting (Figure 1).

Figure 1: Rate of return to (standardized) math skills for individuals with a vocational qualification



Notes: The graph is based on the point estimates of the coefficient on math skills by years of labor market experience (Table 9, Models 2 and 4). Math skills are standardized.

We also shed light on a potentially important bias due to measurement error when estimating returns to math skills based on standardized competency measures. In our sample, the rate of return to math skills increases by at least a magnitude of three when using final math grades from compulsory schooling transcripts as an instrument for the standardized math competencies that are assessed in the context of the NEPS data. Our approach differs in an important aspect from Hanushek et al. (2015), who use reading literacy scores as an instrument for numeracy scores. While the PIAAC data do not include an additional measure for numeracy skills, we have information about the final math grades in 9th grade, which we use as an instrumental variable. This choice of instrument is logically more coherent with our objective, considering that final math grades are a direct indicator of an individual's mathematical skills, making them a more appropriate and specific proxy for math skills compared to reading. This methodological variation is reflected in our findings, which indicate larger differences in the coefficients' size, suggesting a more substantial association of math skills with wage development than previously estimated.[13]

Our results also speak directly to another strand of the literature that attempts to distinguish signaling and human capital effects. Aryal et al. (2022) use Norwegian administrative data and find that 30% of the returns to education can be attributed to the signaling value of education, which is mainly accumulated during the first five years after an individual enters the labor market (Aryal et al. 2022, p. 1693). Although we cannot replicate their identification strategy, our results are in line with their findings, as we also find evidence for a very high initial rate of return to human capital (i.e., math skills in our case), which declines, however, rather quickly in the first five years on the labor market. Moreover, when we include firm characteristics, the initial rate of return to math skills in the first year drops from 36% to 15%, indicating that an important part of the signaling value of math skills is that high-ability apprentices are sorted into high-wage firms already at the beginning of their apprenticeship, and thus have a substantial earnings advantage at the beginning of their career (Figure 1).

Finally, our results contribute to the literature on the gender pay gap. We first document a strong gender gap regarding the selection into low-quality employers, characterized by lower average pay, lower AKM rank, and smaller firm size. However, in line with Lazear and Rosen (1990), we find that once we control for the occupational field, gender is no longer significantly associated with the quality of the training firm. Despite that, we find evidence for a persistent gender pay gap of almost 10% on average, when women enter the skilled labor market after having obtained their vocational qualification, even when controlling for the occupational field and other observable cognitive and non-cognitive skills. When accounting for firm characteristics, including firm AKM effects and firm size, the gender pay gap decreases to 6%. Thus, while we can show that the initial employer quality is not different for women than for men when accounting for the occupational choice, women still face a significant wage penalty after having completed their vocational training within a given occupational field. However, we leave it to future research to identify the reasons for this outcome.

[13] We also estimated a model using reading skills as an instrument for math skills. Although the two measures are strongly correlated, the respective second stage coefficients of math skills were considerably smaller compared to our estimates when using math grades as an instrument for math skills. Intuitively, using two different measures for an individual's math competency, we can exploit the common variation in the two variables that is, however, purged of the measurement error.

7. Conclusions

In conclusion, our study provides valuable insights regarding the association of math skills, the selection of individuals in training firms, and the subsequent wage development after having acquired a vocational qualification in the context of the German dual apprenticeship system. We find that mathematical skills are an important driver in shaping early career outcomes. Math skills are not only important in aiding school leavers to sort in high-quality training firms and thereby contribute to an increase in allocation efficiency, but also generate a substantial wage return, particularly in the first years as skilled workers. Finally, we also highlight the potentially large attenuation bias that can arise due to measurement errors in standardized skills test. Exploiting the availability of two measures of the same competency, we could demonstrate that the rate of return to math skills increases by at least a factor of three.

While context-specific nature of our study may possibly limit the generalizability of findings to other educational and labor market systems with different characteristics, our findings hold significant implications for educational policy and workforce development in Germany. The pronounced association of cognitive skills, especially in mathematics, with both training firm selection and early wage development, underscores the importance of acquiring such skills in secondary school. This highlights the need for educational systems to place a strong emphasis on developing robust mathematical competencies. Future research should explore the long-term effects of both cognitive and non-cognitive skills on career advancement and earnings, extending beyond the initial employment phase. This will be feasible using NEPS data, as it allows for the tracking of participants throughout their future careers.

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Tables

Table 1: Descriptive Statistics for the Full Sample of Apprentices

Variable	Obs		Mean		Std. dev.		Min		Max	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Math competency	778	1,258	-.609	-.072	.794	1.018	-3.222	-2.587	2.535	4.543
Reading competency	778	1,258	-.346	-.385	1.041	1.117	-3.178	-3.879	3.300	3.300
ICT competency	778	1,258	-.296	-.163	.769	.897	-2.658	-3.300	2.430	2.909
Perceptual speed	778	1,258	60.269	56.122	13.712	14.289	19	3	93	93
Reasoning competency	778	1,258	8.015	8.341	2.379	2.485	0	0	12	12
Conscientiousness	778	1,258	3.369	3.035	.822	.831	1	1	5	5
Openness	778	1,258	3.553	3.251	.893	.939	1	1	5	5
Extraversion	778	1,258	3.427	3.415	.919	.869	1	1	5	5
Agreeableness	778	1,258	3.591	3.413	.638	.668	1	1	5	5
Neuroticism	778	1,258	2.951	2.605	.819	.843	1	1	5	5
Prosocial behavior	778	1,258	7.952	7.006	1.652	1.973	0	0	10	10
9th grade math grade	778	1,258	3.737	3.951	.934	.950	1	1	6	6
Training completion	778	1,258	.614	.642	.487	.479	0	0	1	1

Notes. Firm average daily pay is in Euros. Source: NEPS-SC4-ADIAB.

Table 2: Descriptive Statistics for Graduated Apprentices Subsequently Employed

Variable	Obs		Mean		Std. dev.		Min		Max	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Average daily wage for apprentices	410	788	29.505	30.007	7.673	7.120	9.807	13.136	51.701	54.581
Average daily wage after employment	470	872	78.367	84.891	20.822	19.215	14.070	15.895	125.661	124.684
Firm average daily pay (full-time employees)	470	872	105.230	111.195	39.266	37.278	38.11	33.07	265.59	317.25
Movers (leave training firm after graduation)	470	872	.422	.391	.494	.488	0	0	1	1

Notes. Wages are in Euros. Source: NEPS-SC4-ADIAB.

Table 3: Descriptive Statistics by Occupation: Gender Share, Daily Wage, and Math Scores

Occupational fields	Share of female			Average Daily Wage			Math		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Occupations in agriculture, forestry, and horticulture	.24	.44	21	72.06	14.94	21	-.42	.51	21
Manufacturing occupations	.07	.25	177	86.74	19.34	177	.00	.90	177
Occupations concerned with production technology	.06	.23	301	87.64	20.19	301	.24	.97	301
Occupations in building and interior construction	.02	.13	116	83.82	12.50	116	-.03	1.14	116
Occupations in the food industry, in gastronomy and in tourism	.42	.50	62	68.76	14.41	62	-.07	1.07	62
Medical and non-medical health care occupations	.89	.31	200	77.70	21.92	200	-.43	.89	200
Service occupations in social sector and cultural work	.86	.36	21	95.02	16.21	21	-.35	.78	21
Occupations in commerce and trade	.52	.50	108	68.56	14.88	108	-.27	.82	108
Occupations in business management and -organization	.70	.46	102	78.61	19.16	102	-.01	.97	102
Business related service occupations	.71	.46	78	84.73	15.52	78	.22	.93	78
Service occupations in the IT-sector and the natural sciences	.23	.43	52	90.48	20.52	52	.51	1.13	52
Occupations in traffic and logistics	.15	.36	92	76.36	19.36	92	-.21	.85	92
Total	.35	.48	1342	81.57	19.86	1342	-.04	.98	1342

Notes. This table includes the apprentices who finished apprenticeship and got employed. The daily wages are in Euros. The math score is standardized. Source: NEPS-SC4-ADIAB.

Table 4: Daily Wage by Quantile of 9th-Grade Math Performance and Years of Employment

	Employment experience after having obtained vocational qualification				
	1 year	2 years	3 years	4 years	5 years
1st quartile of math skills in grade 9					
Mean	76.636	79.611	81.522	83.884	85.811
Standard deviation	20.088	20.001	20.177	19.406	19.221
Observations	483	480	462	375	301
2nd quartile of math skills in grade 9					
Mean	80.377	85.079	85.793	89.526	89.562
Standard deviation	20.374	18.054	18.425	16.531	16.864
Observations	383	356	326	258	189
3rd quartile of math skills in grade 9					
Mean	83.723	84.582	86.798	88.882	90.24
Standard deviation	18.954	19.394	18.868	18.109	19.752
Observations	317	290	275	215	158
4th quartile of math skills in grade 9					
Mean	87.866	91.000	92.127	93.285	94.881
Standard deviation	19.843	17.497	19.889	19.198	16.093
Observations	186	176	153	107	67

Notes: Daily wages are in Euros. Source: NEPS-SC4-ADIAB

Table 5: Selection in training firms

	Training Firm AKM Rank		Training Firm Size		Training firm average log daily wage		Average log daily apprentice wage	
	Males	Females	Males	Females	Males	Females	Males	Females
9th grade math grade	.441***	.353	.181***	.093	.032***	.027*	.029***	.017
	(.164)	(.219)	(.055)	(.071)	(.010)	(.015)	(.008)	(.011)
Reading competency	.343*	.403	.192***	.295***	.023*	.047**	.020**	.039***
	(.201)	(.271)	(.065)	(.095)	(.012)	(.019)	(.009)	(.013)
ICT competency	.313	.521*	.174***	.026	.032***	.045**	.015*	.005
	(.197)	(.291)	(.065)	(.086)	(.012)	(.018)	(.008)	(.014)
Perceptual speed	-.178	-.205	-.086	.004	-.009	-.010	.000	-.011
	(.162)	(.208)	(.051)	(.067)	(.010)	(.014)	(.007)	(.010)
Reasoning competency	.080	.705***	-.063	.149**	.001	.057***	.000	.032***
	(.177)	(.237)	(.059)	(.075)	(.010)	(.016)	(.008)	(.011)
Conscientiousness	.275	.261	.066	-.072	.0325**	.005	.017**	.009
	(.174)	(.230)	(.057)	(.073)	(.011)	(.015)	(.008)	(.011)
Openness	.011	-.368*	.004	-.049	.005	-.021	-.008	-.026**
	(.166)	(.223)	(.053)	(.065)	(.010)	(.016)	(.008)	(.011)
Extraversion	-.084	.426*	-.015	.043	.002	.028*	-.001	.002
	(.160)	(.218)	(.052)	(.061)	(.010)	(.015)	(.007)	(.010)
Agreeableness	-.107	.098	.074	.031	-.001	.013	-.001	.009
	(.165)	(.246)	(.053)	(.071)	(.010)	(.017)	(.008)	(.011)
Neuroticism	-.440**	.152	-.044	.097	-.018*	.019	-.005	.006
	(0.161)	(.225)	(.050)	(.066)	(.010)	(.014)	(.007)	(.010)
Prosocial behavior	.249	.101	.006	.178**	.010	.031	.014*	.010
	(.160)	(.270)	(.052)	(.081)	(.010)	(.020)	(.007)	(.013)
Constant	10.86***	9.871***			4.606***	4.519***	3.351***	3.334***
	(.166)	(.250)			(.010)	(.017)	(.008)	(.011)
Observations	1211	732	1258	778	1214	744	1258	778
R^2	.031	.058			.041	.093	.038	.058

Notes. Cluster-robust standard errors in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Firm size is a categorical variable, and the coefficients are based on an ordered logit model. The coefficients of other cognitive and non-cognitive variables were not significant in this estimation. Source: NEPS-SC4-ADIAB.

Table 6: Selection in training firms and the role of occupational controls

	Training Firm AKM Rank		Training Firm Size		Training firm average log daily wage		Average log daily apprentice wage	
9th grade math grade	.421***	.318**	.151***	.137***	.032***	.024***	.025***	.025***
	(.101)	(.127)	(.043)	(.044)	(.008)	(.008)	(.006)	(.006)
Reading competency	.379**	.334**	.221***	.192***	.031***	.026***	.027***	.024***
	(.162)	(.158)	(.053)	(.054)	(.010)	(.010)	(.008)	(.008)
ICT competency	.365**	.203	.112**	.076	.034***	.017*	.011	.007
	(.164)	(.157)	(.051)	(.052)	(.010)	(.009)	(.007)	(.007)
Perceptual speed	-.177	-.183	-.056	-.076*	-.010	-.008	-.004	-.005
	(.128)	(.122)	(.040)	(.040)	(.008)	(.007)	(.006)	(.006)
Reasoning competency	.304**	.295*	.017	.027	.022**	.019**	.012*	.013**
	(.142)	(.137)	(.045)	(.046)	(.009)	(.008)	(.007)	(.006)
Conscientiousness	.270*	.244*	.016	.033	.018**	.014*	.014**	.014**
	(.138)	(.133)	(.045)	(.044)	(.009)	(.008)	(.006)	(.006)
Openness	-.031	-.070	-.016	.000	-.004	.001	-.015**	-.012**
	(.133)	(.128)	(.040)	(.042)	(.009)	(.0008)	(.006)	(.006)
Extraversion	.114	.134	.007	.028	.009	.011	.000	.000
	(.130)	(.126)	(.040)	(.040)	(.009)	(.008)	(.006)	(.006)
Agreeableness	-.025	-.021	.061	.030	.005	.005	.003	.003
	(.138)	(.133)	(.042)	(.042)	(.008)	(.008)	(.006)	(.006)
Neuroticism	-.234*	-.217	.004	.022	-.006	-.004	-.001	-.001
	(0.131)	(.128)	(.040)	(.040)	(.008)	(.008)	(.006)	(.006)
Prosocial behavior	.194	.185	.057	.078*	.015*	.015*	.013**	.013**
	(.138)	(.133)	(.043)	(.044)	(.009)	(.008)	(.007)	(.007)
Female	-1.044***	.168	-.257***	-.123	-.090***	.010	-.021	-.028*
	(.288)	(.332)	(.092)	(107)	(.019)	(.021)	(.013)	(.016)
Occupations	No	Yes	No	Yes	No	Yes	No	Yes
Constant	10.88***	6.231***			4.608***	4.273***	3.351***	3.205***
	(.164)	(.865)			(.010)	(.059)	(.007)	(.027)
Observations	1943	1943	2036	2036	1958	1958	2036	2036
R^2	.044	.127			.066	.202	.042	.070

Notes. Cluster-robust standard errors in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Firm size is a categorical variable and the coefficients based on an ordered logit model. The coefficients of other cognitive and non-cognitive variables were not significant in this estimation. Source: NEPS-SC4-ADIAB.

Table 7: Post-training wage development

	Model 1			Model 2			Model 3			Model 4		
	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female	All
Math × 1 year experience	.049***	.074***	.056***	.045***	.038*	.042***	.042***	.044**	.040***	.012**	.016	.011**
	(.008)	(.015)	(.007)	(.010)	(.021)	(.009)	(.010)	(.021)	(.009)	(.006)	(.011)	(.005)
Math × 2 years experience	.044***	.059***	.046***	.044***	.027	.036***	.039***	.038**	.036***	.014**	.000	.008
	(.008)	(.017)	(.007)	(.009)	(.019)	(.009)	(.009)	(.019)	(.0008)	(.006)	(.011)	(.005)
Math × 3 years experience	.023**	.066***	.037***	.018	.051**	.030**	.014	.057**	.028**	.002	.033***	.012
	(.010)	(.017)	(.009)	(.011)	(.024)	(.012)	(.011)	(.024)	(.012)	(.008)	(.012)	(.008)
Math × 4 years experience	.030***	.044**	.034***	.036***	.038*	.035***	.030***	.041*	.030***	.016**	.019	.016**
	(.009)	(.020)	(.0008)	(.011)	(.023)	(.010)	(.010)	(.021)	(.009)	(.007)	(.019)	(.007)
Math × 5 years experience	.027**	.041**	.033***	.027*	.009	.023**	.021	.016	.017	.019**	.008	.015*
	(.011)	(.020)	(.009)	(.014)	(.024)	(012)	(.013)	(.022)	(.011)	(.009)	(.018)	(.008)
Female			-.086***			-0.096***			-.088***			-.057***
			(.012)			(.013)			(.016)			(.011)
Competences × experience	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
General intelligence × Experience	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
Non-cognitive skills × experience	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
Occupations	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes
Firm attributes	no	no	no	no	no	no	no	no	no	yes	yes	yes
Observations	3601	2219	5820	3601	2219	5820	3601	2219	5820	3557	2194	5751
R^2	.063	.076	.090	.088	.117	.108	.158	.229	.193	.607	.633	.617

Notes. Cluster-robust standard errors in parentheses. ∗∗∗ Significant at the 1% level; ∗∗ significant at the 5% level; ∗ significant at the 10% level. Firm size is a categorical variable, and the coefficients are for an ordered logit model. The coefficients of other cognitive and non-cognitive variables were not significant in this estimation. Source: NEPS-SC4-ADIAB.

Table 8: Post-training wage development, movers vs. stayers

	Model 1		Model 2		Model 3		Model 4	
	Stayers	Movers	Stayers	Movers	Stayers	Movers	Stayers	Movers
Math × 1 year experience	.051***	.059***	.038***	.043***	.035***	.047***	.011*	.011
	(.009)	(.012)	(.011)	(.015)	(.011)	(.015)	(.006)	(.009)
Math × 2 years experience	.043***	.050***	.031***	.040***	.032***	.041***	.008	.006
	(.009)	(.010)	(.011)	(.014)	(.010)	(.013)	(.007)	(.009)
Math × 3 years experience	.033***	.044***	.027	.034**	.026	.032**	.010	.013
	(.012)	(.012)	(.017)	(.015)	(.017)	(.015)	(.010)	(.009)
Math × 4 years experience	.031***	.039***	.027**	.050***	.022**	.051***	.008	.035***
	(.011)	(.013)	(.012)	(.018)	(.011)	(.017)	(.009)	(.011)
Math × 5 years experience	.035***	.030*	.025*	.021	.018	.021	.014*	.018
	(.011)	(.017)	(.014)	(.021)	(.012)	(.019)	(.008)	(.015)
Female	-.099***	-.063***	-.114***	-.067***	-.092***	-.085***	-.046***	-.066***
	(.015)	(.021)	(.016)	(.021)	(.019)	(.027)	(.013)	(.019)
Other skills	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Occupations	No	No	No	No	Yes	Yes	Yes	Yes
Firm attributes	No	No	No	No	No	No	Yes	Yes
Observations	3724	2096	3724	2096	3724	2096	3683	2068
R^2	.091	.101	.115	.126	.216	.223	.629	.627

Notes: Dependent variable: log daily wage. Other control variables include reading, ICT, general cognition, and non-cognitive skills. Cluster-robust standard errors in parentheses. $***$ Significant at the 1% level; $**$ significant at the 5% level; $*$ significant at the 10% level. Source: NEPS-SC4-ADIAB.

Table 9: Post-training wage development - instrumental variables regression (full sample)

		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N
Experience: 1 year	.233*** (.053)	37.097	1217	.305*** (.085)	25.478	1217	.278*** (.083)	23.878	1217	.141** (.057)	19.303	1204
Experience: 2 years	.153*** (.039)	49.816	1238	.188*** (.058)	39.035	1238	.190*** (.058)	35.939	1238	.082** (.041)	28.919	1223
Experience: 3 years	.137*** (.050)	37.610	1165	.148** (.066)	34.453	1165	.138** (.066)	32.128	1165	.080* (.042)	30.054	1152
Experience: 4 years	.060 (.039)	39.051	915	.062 (.056)	29.494	915	.044 (.055)	25.313	915	.054 (.036)	24.684	904
Experience: 5 years	.084* (.043)	31.851	700	.080 (.064)	26.888	700	.095 (.065)	24.254	700	.107** (.050)	22.798	692
Other skills		No			Yes			Yes			Yes	
Occupations		No			No			Yes			Yes	
Firm attributes		No			No			No			Yes	

Notes. Dependent variable: log daily wage. Other control variables include reading, ICT, general cognition, and non-cognitive skills. Cluster-robust standard errors in parentheses. Instrument: math grades in 9th grade. Results of the first stage regression available upon request.∗∗∗ Significant at the 1% level; ∗∗ significant at the 5% level; ∗ significant at the 10% level. Source: NEPS-SC4-ADIAB.

Table 10: Post-training wage development - instrumental variables regression (male subsample)

		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N
Experience: 1 year	.256*** (.094)	10.732	797	.350*** (.132)	10.124	797	.303** (.125)	9.253	797	.117 (.082)	6.561	786
Experience: 2 years	.151*** (.053)	18.965	769	.181** (.075)	15.974	769	.138* (.077)	13.623	769	-.002 (.059)	10.540	762
Experience: 3 years	.074 (.073)	9.747	693	.064 (.082)	13.139	693	.047 (.080)	13.129	693	-.012 (.057)	12.868	685
Experience: 4 years	.118** (.059)	15.357	548	.148* (.076)	14.400	548	.131* (.071)	13.535	548	.067 (.045)	13.035	542
Experience: 5 years	.134** (.062)	13.409	427	.168* (.087)	12.444	427	.180** (.080)	14.223	427	.131** (.056)	13.976	421
Other skills		No			Yes			Yes			Yes	
Occupations		No			No			Yes			Yes	
Firm attributes		No			No			No			Yes	

Notes. Dependent variable: log daily wage. Other control variables include reading, ICT, general cognition, and non-cognitive skills. Cluster-robust standard errors in parentheses. Instrument: math grades in 9th grade. Results of the first stage regression are available upon request. ∗∗∗ Significant at the 1% level; ∗∗ significant at the 5% level; ∗ significant at the 10% level. Source: NEPS-SC4-ADIAB.

Table 11: Post-training wage development - instrumental variables regression (female subsample)

		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N		F-stat. (IV)	N
Experience: 1 year	.206*** (.062)	47.899	420	.210** (.100)	20.786	420	.201** (.096)	19.812	420	.151** (.072)	17.516	418
Experience: 2 years	.144*** (.055)	46.767	469	.153* (.083)	35.366	469	.215** (.085)	30.608	469	.134** (.060)	24.166	461
Experience: 3 years	.196*** (.066)	44.407	472	.240** (.101)	29.328	472	.253** (.104)	25.125	472	.176*** (.062)	21.171	467
Experience: 4 years	.007 (.056)	28.494	367	-.028 (.096)	16.163	367	-.018 (.101)	12.931	367	.094 (.067)	12.051	362
Experience: 5 years	.035 (.065)	21.297	273	.003 (.101)	15.933	273	.008 (.115)	11.026	273	.099 (.090)	10.087	271
Other skills		No			Yes			Yes			Yes	
Occupations		No			No			Yes			Yes	
Firm attributes		No			No			No			Yes	

Notes. Dependent variable: log daily wage. Other control variables include reading, ICT, general cognition, and non-cognitive skills. Cluster-robust standard errors in parentheses. Instrument: math grades in 9th grade. Results of the first stage regression are available upon request. $***$ Significant at the 1% level; $**$ significant at the 5% level; $*$ significant at the 10% level. Source: NEPS-SC4-ADIAB.