The Value of Early-Career Skills

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Abstract

We develop novel measures of worker skills that depict the full range and intensity of human capital at labor market entry. We exploit that skill requirements of apprenticeships in Germany are codified in state-approved, nationally standardized apprenticeship plans. These plans provide more than 13,000 different skills and the exact duration of learning each skill. Following workers over their careers in administrative data, we find that cognitive, social, and digital skills acquired during apprenticeship are highly – yet differently – rewarded. We also document rising returns to digital and social skills since the 1990s, while returns to cognitive skills have increased only moderately.

Keywords: returns to skills, apprenticeship plans, labor market, earnings, early-career skills

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1. Introduction

Individuals' human capital is essential for their success on the labor market. A substantial literature, starting with the seminal contributions by Schultz (1961), Becker (1962), and Mincer (1974), has analyzed the labor market returns to human capital. More recent research has shown that human capital is also important to understand workers' occupational choices (Deming, 2017; Deming and Noray, 2020), career patterns (Hanushek et al., 2017; Adda and Dustmann, 2022; Arellano-Bover, 2022), and susceptibility to technological change (Cortes, 2016; Braxton and Taska, 2023). However, even after 60 years of investigating the economic value of human capital, there is still a lack of adequate data on workers' skills, particularly on their early-career skills.

Most existing studies rely on school attainment measures, such as years of schooling, which has been a pragmatic choice based on data availability (see Deming, 2022, for a recent overview of the literature). However, the limitations of attainment measures are also evident. Most importantly, they provide only a crude approximation of human capital and skills developed at any level of schooling vary widely. An alternative approach measures human capital through skills evaluated in assessment tests for adults (e.g., Hanushek et al., 2015) or children (e.g., Hanushek and Woessmann, 2015). This approach, while generally interesting, also has a number of drawbacks. First, even skill assessments for adults are typically not designed to capture skills learnt or required at the workplace, but rather reflect knowledge acquired at school. Moreover, tested skills cover only a very limited portion of an individual's complete set of skills, mostly basic skills in numeracy and literacy.[1] Another stream of research has used surveys of workers or experts (e.g., O*NET) to estimate the economic value of job tasks (for an overview, see Autor, 2013). However, these data only provide the average task composition of occupations, hence failing to accurately reflect the skills of a substantial portion of workers performing the tasks in those occupations.[2]

In this paper, we develop novel measures of workers' early-career skills that are directly relevant to the labor market, comprehensive, and highly detailed. To do so, we

[1]Returns to such cognitive skills elicited by achievement tests at school or even kindergarten have frequently been studied in the U.S. by following tested individuals into their initial jobs (e.g., Murnane et al., 1995, 2000; Chetty et al., 2011, 2014).

[2]Recently, the use of online job ads to determine the necessary skills for a particular job has become common (e.g., Hershbein and Kahn, 2018). However, these ads only reflect the preferences of employers and do not provide any information about the actual skills of the hired workers. Employers may also omit certain skill requirements if they believe them to be evident from the degree requirement (Carnevale et al., 2014). Furthermore, since job ads typically do not specify the appropriate age or career level for an advertised position, it is not possible to infer early-career skills from them.

exploit the unique setting of the German apprenticeship system, which has three major advantages for the measurement of skills and the analysis of their labor market potential.[3] First and foremost, skill requirements are codified in state-approved, nationally standardized apprenticeship plans.[4] This standardized system ensures that a given apprenticeship imparts the same practical and theoretical skills regardless of the training location in Germany.[5] Importantly, the plans specify the exact number of weeks a skill is learnt, yielding a measure of skill intensity that is straightforward to interpret. Second, our skill measures are highly relevant to the German labor market as approximately 60% of the workforce in Germany has completed apprenticeship training (IAB, 2017).[6] Third, pursuing an apprenticeship typically comes directly after formal schooling, so apprenticeship plans provide a reliable indicator of individuals' skills at the start of their careers.

On average, apprenticeship plans consist of 7 pages and 850 words, thus offering an exceptionally comprehensive and precise description of the skills imparted through apprenticeships. In total, we derive more than 13,000 detailed skills from 165 plans, which cover more than 85% of the workforce that has completed apprenticeship training. Skills encompass both general skills, such as teamwork and conflict resolution, and job-specific skills, such as managing databases and operating transport equipment. We categorize these narrowly defined skills into broader categories using the skill classification by Deming and Kahn (2018). This procedure results in six broader skill domains, comprising the complete skill set of trained workers: cognitive, social, digital, manual, management, and administrative. We show that there is considerable heterogeneity in these early-career skills even for individuals with the same level of human capital judged by existing measures such as test scores or years of schooling.

To understand how workers' early-career skills affect future labor market success, we study how skills developed through apprenticeship are rewarded over workers' careers. Estimations are based on administrative German labor market data from the Institute of Employment Research (IAB) that cover workers' full employment histories in the period 1990-2017. The data provide detailed information about wages, employment, and occupations, including the apprenticeship occupation to which we can link our skill measures.

[3]The approach of using apprenticeship curricula to infer worker skills has been pioneered by Eggenberger et al. (2018) for Switzerland. Using the skill-weights approach by Lazear (2009), they document higher returns to more skill-specific apprenticeship occupations.

[4]Each apprenticeship plan refers to an occupation, i.e., standards are set at the occupational level.

[5]The nationwide standardization distinguishes apprenticeship plans from university curricula (e.g., Biasi and Ma, 2022), which are neither harmonized nor standardized across universities.

[6]Among workers without a tertiary degree, even three-quarters have obtained an apprenticeship.

We condition the returns-to-skills estimates on a rich set of worker and apprenticeship characteristics. For instance, we control for the year of apprenticeship completion, which absorbs unobserved effects that equally affect all workers in a given year (e.g., general economic conditions and cohort effects). We also control for the county of the training company, picking up regional differences in training quality, industry structure, and labor demand at a fine spatial level. Moreover, we only compare workers who completed their apprenticeship in the same occupational field at the 1-digit level (e.g., comparing bank clerks and insurance clerks, gardeners and florists, or software developers and IT clerks).

We find that workers who obtained higher cognitive, social, or digital skills during apprenticeship fare better on the labor market over long-run horizons.[7] In the first years after apprenticeship completion, all three skill domains are only weakly related to wages. However, skill returns increase substantially over workers' careers. At the end of our observation window, 16-20 years after labor market entry, one additional month of learning cognitive skills is associated with 1.3% higher wages. Returns to social and digital skills are even larger, as one additional month of acquiring these skills pays 1.5% and 2.1% higher wages, respectively. These one-month skill returns amount to 16%-27% of the return to a full *year* of schooling, indicating the economic relevance of our returns-to-skills estimates.[8]

Furthermore, we demonstrate that workers who completed an apprenticeship that provided both higher cognitive and social skills are particularly valuable on the labor market, indicating skill complementarities. This is consistent with U.S. evidence provided by Weinberger (2014), Deming (2017), and Deming and Kahn (2018), and with evidence for Switzerland by Kiener et al. (2023). Using job vacancy data from Lightcast, we also show that returns to skills are related to firms' regional skill demand: In particular, workers who acquired more cognitive skills earn higher wages in regions in which firm technology is such that the job likely requires these skills.

Our pattern of results is robust to various ways of addressing selection into apprenticeships. For instance, higher-ability workers may be more likely to complete certain apprenticeships, which would lead to a correlation of apprenticeship skills and wages that cannot be interpreted as a causal effect. Moreover, family background, personality traits, or characteristics of the apprenticeship establishment could directly influence earnings; if also related to apprenticeship skills, these could lead to standard omitted variable bias in the analysis of returns to skills. We provide several analyses to address these concerns.

[7] In contrast, higher manual, management, or administrative skills do not improve career prospects.

[8] Most apprenticeships take three years to complete. On average, workers acquire 13.1 months of cognitive skills, 4.6 months of social skills, and 2.1 months of digital skills through apprenticeship training.

First, we leverage complementary survey data that provide rich information on workers' high-school grades, non-cognitive skills, and the education and occupation of their parents. These family background controls are particularly important in the case of Germany due to its high intergenerational persistence of economic success (OECD, 2018). Second, to account for the possibility of worker sorting into more productive establishments, we control for additional characteristics of the establishment of apprenticeship completion in our administrative data (i.e., age, size, industry, and a direct measure of productivity). We also identify returns from within-establishment variation, thus only comparing workers who finished their apprenticeship in the same establishment, year, and occupational field. Additionally, we provide evidence that estimated returns to early-career skills not merely reflect returns to working in specific occupations.

Finally, we examine trends in the wage returns to cognitive, social, and digital skills over almost 30 years. We document a remarkable rise in the returns to all three skill domains between 1990 and 2017. We observe the fastest increase for returns to digital skills, which coincided with the rise of computers in the economy (e.g., Borghans and ter Weel, 2007). This suggests that computers increase the marginal product of workers with complementary skills. We also find that returns to social skills have increased faster than returns to cognitive skills, corroborating the findings from Edin et al. (2022) for Sweden and Koomen and Backes-Gellner (2022) from Switzerland. Other research has emphasized that rising demand for social skills has been a major driver of trends in employment and earnings (e.g., Deming, 2017; Atalay et al., 2020; Hansen et al., 2021). However, empirical investigations of these patterns typically use data from online job vacancies, which are mostly targeted at professional workers. Our results show that the value of social skills has also increased in low- and middle-wage jobs.[9]

Our paper contributes to the literature on returns to skills in various ways. Our first key contribution is measurement. We depict workers' complete range of skills developed through multi-year apprenticeships, which directly reflect the skills required for a job. We further use novel information on the weeks of learning each skill, provided by the apprenticeship plans, which allows us to construct easily interpretable skill intensity measures in the spirit of years of schooling. A related stream of literature uses apprenticeship plan data for Switzerland to investigate the returns to specific skills (self-competence, social skills, and IT skills) on the Swiss labor market, see Kiener et al. (2022), Kiener et al. (2022), or Kiener et al. (2023). However, none of these studies provide a full depiction of

[9]This result is in line with recent U.S. survey evidence from Heller and Kessler (2022).

early-career skills using all available skill information from the apprenticeship plans nor do they have information on the exact duration of learning a specific skill.

Second, we link our skill measures to administrative data to study the sources of labor market returns to vocational education (Kiener et al., 2022; Adda and Dustmann, 2022; Silliman and Virtanen, 2022; Kiener et al., 2023). We show that different types of skills acquired during apprenticeship are differently valued over workers' careers. We relate these differential returns to complementarities between skills and between skills and technology proxied by firms' skill demand from job ad data. Finally, by virtue of the long time coverage of our administrative data, we show trends in returns to cognitive, social, and digital skills specifically for low- and medium-educated workers.

The remainder of the paper is structured as follows. Section 2 describes the German apprenticeship system and Section 3 explains how we derive our skill measures from the apprenticeship plans. Sections 4 and 5 introduce the data and the empirical model, respectively. Section 6 reports the wage returns to early-career skills throughout workers' careers, Section 7 examines potential drivers of these returns, and Section 8 addresses selection into apprenticeships. Section 9 documents changes in returns to skills in Germany over the last three decades. Section 10 concludes.

2. Institutional Setting

This section outlines the institutional features of the German apprenticeship system, which provide the basis for the derivation of our skill measures.

Apprenticeship graduates account for a large part of the German labor force. In 2017, the last year of our observation window, about 60% of workers had completed apprenticeship training and 1.5 million apprentices were in vocational education (IAB, 2017; BIBB, 2017b).[10] Individuals typically start an apprenticeship after finishing secondary school when they are between 16 and 20 years old. Apprenticeship training is targeted at graduates from higher-track or lower-track secondary schools, who directly apply for an apprenticeship at a training firm.[11] In our data, 92.8% of trained workers obtained a lower

[10]More precisely, for 58.8% of workers subject to social security, completed apprenticeship training was the highest level of education in 2017 (IAB, 2017). This figure does not include workers who have obtained a higher educational degree after their apprenticeship and is thus likely an underestimation of the actual share of workers with apprenticeship in the German workforce. However, available data typically only report the highest level of education attained.

[11]In Germany, students switch into differing-ability secondary school tracks by age 10: lower secondary school ("Hauptschule"), intermediate secondary school ("Realschule"), and upper secondary school ("Gymnasium"). Completing any of these school tracks qualifies for starting an apprenticeship, while

or intermediate secondary school degree before the apprenticeship and 7.2% obtained an upper secondary school degree. Thus, individuals enter the apprenticeship system with very similar levels of education. Entry barriers into apprenticeship are generally very low (in contrast to university education, which is much more selective). Labor market returns to measured apprenticeship skills are thus arguably less attributable to previously acquired skills and knowledge, but rather reflect genuine effects of apprenticeship training.

The German apprenticeship system has an exceptional international reputation due to its combination of theory and practice in the form of a "dual system": An apprenticeship consists of on-the-job-training in firms (3-4 days per week) and education at public vocational schools (1-2 days per week). The skills learnt during apprenticeship training in firms and vocational schools are codified in state-approved apprenticeship plans.[12] Apprenticeship plans are developed jointly by employers' associations, experts from the vocational training sector, and the *Federal Institute for Vocational Training (BIBB)*, and are signed into law by the federal government (see BIBB, 2017a). Overall, apprenticeship plans provide the regulatory framework for 327 different occupations (as of 2017).

Most important for our paper is that all apprenticeships are standardized across Germany by the *Vocational Training Act*. This act specifies that training firms have to make sure that they adhere to the requirements stated in apprenticeship plans, to ensure the quality of apprenticeship training and the transferability of skills across regions and firms (Janssen and Mohrenweiser, 2018). Thus, there is a nationally standardized plan for every apprenticeship occupation and uniform examination rules for apprentices across whole Germany exist. Exams in a particular apprenticeship take place on the same day throughout Germany and these exams are monitored and graded by the Chamber of Commerce and Industry (IHK) or the Chamber of Crafts (HK), ensuring compliance with the nationwide standards. Due to this highly standardized environment, apprenticeship training in a particular occupation conveys the same general and occupation-specific skills throughout Germany, since all firms have to adhere to the content stated in the apprenticeship plans.[13]

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upper secondary education is required for entry into university. Our estimations control for the highest educational degree that was obtained before starting an apprenticeship.

[12]The school-level education and firm training are both regulated in corresponding apprenticeship plans that are synchronized with each other. Due to this high synchronization, we resort to the firm training plans since they provide considerably more detail than the school plans and also allow to measure skills learnt in weeks (see Section 3).

[13]Germany also offers apprenticeships regulated outside of the scope of the *Vocational Training Act*. For instance, four health care apprenticeships are covered by the *Nursing Act*. We only focus on appren-

3. Early-Career Skills

This section explains how we construct our measures of early-career skills. We first describe the structure and characteristics of apprenticeship plans from which we derive the skill measures. We then introduce our final skill classification and show simple correlational exercises to confirm the validity of our classification.

3.1. Apprenticeship Plans

As outlined in the previous section, apprenticeship plans provide the factual and temporal structure of apprenticeship training. We have analyzed plans for the 165 largest apprenticeship occupations in Germany, representing more than 85% of the German workforce with completed apprenticeship training.[14] Analyzing apprenticeship plans allows us to derive a comprehensive and precisely measured set of skills developed during the respective apprenticeship. Each plan represents one occupation and consists of an average of 7 pages and 850 words. It specifies the skills which are imparted in the apprenticeship and provides a detailed timeline at which point of the apprenticeship training the respective skill is developed. Plans also state for how long (in weeks) apprentices are learning a specific skill. Thus, plans not only provide information on the skills that are acquired during apprenticeship ("extensive margin"), but also with which intensity these skills are learnt ("intensive margin").

All plans we consider for our analysis have a similar structure. As an example, Figure 1 shows the apprenticeship plan for the occupation "e-Commerce Salesperson". Column 3 is of main interest for our analysis, since it includes a detailed description of skills provided in the apprenticeship. We treat each bullet point (a) to (f) as one distinct skill. Column 4 shows the number of weeks a skill has been learnt. In this example, an apprentice invests 16 weeks in learning the six skills stated in Column 3. To arrive at the intensity for each specific skill, we assume that the 16 weeks are equally divided among the six skills. For expositional purposes, we measure the skill intensity in months by dividing the stated learning duration in weeks by 4.3. Applying this procedure to all apprenticeship plans yields a measure of the early-career skills of trained workers at an unprecedented level of detail and scope.

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ticeships covered by the *Vocational Training Act*, under which the vast majority of apprenticeships in Germany is organized.

[14] We refrained from labeling those occupations in which only a very small share of workers is employed; for instance, hunting ground supervisors had 43 new apprentices in 2017, furriers had 8 new apprentices, and glassmakers had just 3 new apprentices. For these small occupations, we mostly had few or no observations in our worker data (see Section 4).

Figure 1: Example of an Apprenticeship Plan

Seq. Nr	Part of the apprenticeship profile	Skills, knowledge, and abilities to be taught	Temporal references in weeks in	
			Month 1 to 15	Month 16 to 36
1	2	3	4	
1	Selection and usage of online sales channels (§ 4 paragraph 2 number 1)	a) Select and differentiate online sales channels according to scope of services, performance, areas of application, and economic efficiency b) Evaluate user behavior and derive suggestions for improvement for online sales c) Analyze process flows and further develop concept for user-friendly interface d) Adhere to legal regulations and operational requirements, in particular regarding information obligations, competition law, trademark protection, copyright and data protection, when using the online sales channel e) Assess the technical and organizational requirements and framework conditions for the use of new online sales channels in connection with different business models and derive measures f) Cooperate with internal and external service providers in the further development and optimization of online sales systems, define scope of services and control service delivery		16

Notes: Figure shows the apprenticeship plan for an "e-Commerce Salesperson". The plan has been translated from German.

Table 1 presents descriptive statistics of the most important apprenticeship plan characteristics: Length of the apprenticeship training, year of the last plan update, and number of listed skills in a plan. Most apprenticeships take three years (36 months) to complete, but there are also shorter (24 months) and longer (42 months, 48 months) apprenticeships.[15] On average, each plan lists 120 different skills.[16] In total, we have classified 13,472 different skills provided through apprenticeship training. Thus, apprenticeship

[15] 71.3% of apprenticeships in our sample take 36 months to complete, 7.9% take 24 months, 18.3% take 42 months, and 2.4% take 48 months. The duration of training is the same for a given occupation throughout Germany.

[16] Note that the total number of skills varies between apprenticeships: Those apprenticeships with a longer training duration also exhibit a larger number of skills in the plans. However, there is no cap on the maximum number of skills in a plan. This addresses the concern that skills might not be listed due to space constraints in the plans even if they are imparted in the respective apprenticeship.

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max
Apprenticeship plan characteristics				
Length (in months)	36.44	4.62	24	48
Number of detailed skills	120.02	38.45	51	248
Last update	2006	7.01	1979	2019
Skill content (months) at the occupation level				
Cognitive	13.45	5.00	2.31	25.38
Social	3.31	3.05	0.00	17.60
Digital	2.06	2.82	0.00	16.50
Manual	12.98	8.45	0.00	32.60
Management	0.15	0.40	0.00	3.41
Admin	4.61	3.39	0.46	23.88
Skill content (months) at the individual level				
Cognitive	13.05	4.33	2.31	25.38
Social	4.57	3.51	0.00	17.60
Digital	2.13	1.65	0.00	8.90
Manual	11.72	9.62	0.00	32.60
Management	0.18	0.44	0.00	3.41
Admin	6.29	3.24	0.46	12.97

Notes: Statistics are based on the 165 largest apprenticeship occupations in Germany and individual level data from SIAB (see Section 4).

plans provide a more detailed skill distinction than widely used expert databases like the U.S. Occupational Information Network (O*NET) (hundreds of tasks) and its German equivalent BERUFENET (approx. 8,000 tasks) (see Dengler and Matthes, 2018).

As is apparent from Table 1, there is some heterogeneity in the timing of the last plan update: 78% of plans in our sample have received an update since 2000, 36% have been updated after 2010. We always use the most current plan to derive the skill measures. We did so because the structure of the apprenticeship plans has changed over time. Most importantly, in earlier versions of the plans, it was not always common to report the number of weeks a skill had to be learnt, rendering these plans unusable for our analysis. To see whether the most current plan provides a suitable approximation of the skill content of apprenticeships under older plans, we derived skill measures from the penultimate plan for more than half (50.3%) of the apprenticeships in our sample.[17] Skills are highly

[17] We did not prepare previous plans that did not provide the number of weeks a skill had to be learnt during the apprenticeship.

Table 2: Skill Classification

	Keywords and Phrases
Cognitive	Math and statistics, critical/analytical thinking, problem solving and decision making, language, creativity, innovation, economics, accounting, business analysis, evaluation
Social	Teamwork, communication, negotiation, presentation, consultation and advice, customer service, service orientation, time management, adaptability, flexibility, stress tolerance
Digital	Basic computer skills, office software, data analysis, data security, software
Manual	Construction, transportation, general physical activities, maintenance, installation, repairing, tools
Management	Management of personnel and financial resources, project management
Administrative	Writing, scheduling, support activities, law and regulations

correlated between the current and previous plans, with correlations of 0.663 for cognitive skills, 0.765 for social skills, and 0.717 for digital skills. This suggests that skill measures derived from the current plans, which we use throughout the paper, are a reasonable approximation for the skill measures from previous plans.

3.2. Skill Domains

Since it is not feasible to work with almost 13,500 detailed skills, we assign a more general label to the skills listed in the apprenticeship plans. These labels are based on the classification introduced by Deming and Kahn (2018). However, since their focus is on professional occupations, we had to slightly adapt their classification to make it fit to the German apprenticeship context. Compared to Deming and Kahn (2018), we add the domains "administrative" and "manual" since these domains are highly relevant in a low- and middle-wage apprenticeship context. At the same time, we collapsed their various "management" categories into one category, since management is only of minor relevance in most apprenticeship occupations. Doing so, we defined a total of six skill domains.[18]

[18] Almost all apprenticeship plans also mention very basic skills, such as exploiting opportunities for environmentally friendly use of materials or knowing the organizational structure of the apprentice's company. We exclude these skills from our analysis, reducing the total number of detailed skills which we aggregate into the six broad skill domains to 12,492.

Table 2 lists the six skills and provides the corresponding words or phrases from the apprenticeship plans for each category.[19] In particular, cognitive skills comprise math and statistics, critical thinking, problem-solving, and creativity. Social skills include teamwork, communication, and service-oriented skills. Digital skills include both basic computer skills and more advanced skills such as data analysis.

Table 1 provides the mean, standard deviation, minimum, and maximum of our six skill categories. An average apprenticeship imparts 13.5 months of cognitive skills. These skills are also required in a broad range of jobs, as there is no apprenticeship plan that does not train any cognitive skills. Social and digital skills are less common (with means of 3.3 months and 2.1 months, respectively), and are more specific to certain types of occupations.[20] Many apprenticeships are also intense in manual skills; on average, trained workers learn manual skills for 13 months. However, manual skills clearly dominate in occupations such as carpenters (32.6 months), bakers (30.3 months), bricklayers (29.6 months), and concreters (29.4 months).[21]

We motivated our paper by pointing out that existing measures of human capital provide an insufficient picture of individuals' actual range of labor-market-relevant skills. Indeed, we observe a considerable heterogeneity in the skills developed through apprenticeship even for individuals with the same level of human capital judged by existing measures such as test scores or educational attainment. For instance, linking our skill measures with adult skill assessment data from PIAAC (see Section 4.2) and focusing on trained workers with numeracy skills just 0.05 standard deviations (or 5 PIAAC points) around the median, we observe that the number of months of learning cognitive skills ranges from 3 (e.g., carpenter) to 22 (e.g., bookseller) (standard deviation: 5 months), while social skills vary between 0 (e.g., civil engineer) and 18 months (e.g., bank clerks) (standard deviation: 3 months). The skill ranges within the same educational degree are even wider. For instance, for trained workers holding a lower secondary school degree, the number of months in which cognitive skills are learnt range between 2 (baker) and 24 (tax assistant) (standard deviation: 5 months). The number of months of manual skill training even ranges between 0 (e.g., administrative clerk) and 33 (carpenter) (standard

[19] Table A.1 provides examples of exact phrases as they appear in the apprenticeship plans, and to which skill domains they are assigned.

[20] Figure A.1 shows how skills are distributed across occupational groups, and Table A.2 lists examples of apprenticeship occupations that rely most/least heavily on these skills.

[21] As can be seen in the lower part of Table 1, descriptives for the skill measures are very similar in our main estimation sample of full-time employees whom we follow over the first 20 years of their careers (see Section 4).

Table 3: Skill Correlations

Skill Domain	(1)	(2)	(3)	(4)	(5)	(6)
(1) Cognitive	1.000					
(2) Social	–0.021	1.000				
(3) Digital	0.222	0.149	1.000			
(4) Manual	–0.488	–0.551	–0.490	1.000		
(5) Management	–0.018	0.288	0.235	–0.290	1.000	
(6) Admin	0.036	0.446	0.117	–0.588	0.199	1.000

Notes: Skill correlations based on the 165 largest apprenticeship occupations in Germany. Occupation-level correlations are shown.

deviation: 10 months). We also observe large skill ranges for other skill domains and within higher educational degrees.

Skill Correlations and Validation. Table 3 shows bivariate correlations of the six skill domains. Cognitive and social skills almost have a zero correlation, indicating that they cover very different dimensions of a worker's skill set. Cognitive and digital skills are positively correlated, similar to what has been shown by Deming and Kahn (2018) for professional occupations in the U.S. Not surprisingly, manual skills are negatively correlated with all other skill domains, potentially reflecting that manual jobs are often characterized by a high importance of physical tasks.

Figure A.2 plots the cognitive, social, and digital skills in the German apprenticeship system. We observe a substantial amount of variation in the skill content of apprenticeship plans, even within occupational fields. The figure also shows that cognitive and digital skills, although positively correlated, clearly reflect two different skill dimensions: There are apprenticeships with similar levels of cognitive skills but different levels of digital skills and vice versa. The same is true for social and digital skills.

Several validation exercises, relegated to Appendix A.5, show that our skill measures correlate strongly with existing skill classifications from Dengler and Matthes (2018) and Goos et al. (2014) (based on Autor et al., 2003).

Skill Correlations Over the Career. Finally, one may wonder whether the skills workers learnt through the apprenticeship are a good depiction of the set of skills workers need in their future occupations. Making use of the fact that we can observe both the apprenticeship occupation and all occupations after apprenticeship completion in our administrative data (see Section 4), we investigate the transferability of skills over the life cycle. Table 4 shows the correlation of skills learnt during the apprenticeship and the skills required in the occupation a worker holds in the years 1-5, 6-10, 11-15, and 16-20, respectively, after apprenticeship completion. In the full worker sample (Panel A), we observe a strong positive correlation between the skills initially provided through apprenticeship training and the skills a worker needs in her current job. In the first five years after apprenticeship completion, the correlations between early-career skills and current skills range between 0.790 for cognitive skills and 0.874 for social skills. However, even 16-20 years after apprenticeship completion, these correlations still range between 0.553 for digital skills and 0.750 for social skills. This indicates a high degree of skill relatedness between the initial and current occupation, i.e., workers manage to transfer the skills learnt initially to their future jobs.[22]

Importantly, these strong correlations are not just driven by the fact that workers are simply staying in their apprenticeship occupation. When focusing on occupational switchers (Panel B of Table 4), we continue to find strong positive correlations between early-career skills and current skills (years 1-5 after apprenticeship completion: from 0.620 (cognitive skills) to 0.689 (social skills); years 16-20 after apprenticeship completion: from 0.369 (cognitive skills) to 0.500 (social skills)). This suggests that even if workers switch occupations, the new occupation tends to be skill-related to the previous one, which would have been masked by merely comparing job titles. The fact that a worker's initial set of skills is highly predictive of her future skills indicates that our skill measures help categorizing occupations in a meaningful and economically interpretable way.

Next, we assess the economic value of workers' early-career skills, derived from apprenticeship plans, over the life cycle. In this analysis, we focus on cognitive, social, and digital skills. We do so because previous literature discusses these skills as important determinants of labor market outcomes (e.g., Hanushek et al., 2015; Deming, 2017; Falck et al., 2021). They are also prevalent in the literature on the impact of technological change on the labor market and it has been frequently argued that these skills have become increasingly important as computers substitute for a wider range of routine tasks and are complementary to abstract tasks (e.g., Weinberger, 2014; Deming, 2017; Falck et al., 2021).[23]

[22]Note that we can only assess these over-career skill correlations for workers who remain in an apprenticeship occupation.

[23]In Section 9, we document that the returns to cognitive, social, and in particular digital skills have indeed been increasing over the last three decades.

Table 4: Transferability of Skills over the Career

Skill Category	1–5 yrs	6–10 yrs	11–15 yrs	16–20 yrs
A. All workers				
(1) Cognitive	0.790	0.667	0.610	0.563
(2) Social	0.874	0.808	0.778	0.750
(3) Digital	0.817	0.676	0.611	0.552
B. Occupational Switchers				
(4) Cognitive	0.620	0.465	0.388	0.369
(5) Social	0.689	0.567	0.515	0.500
(6) Digital	0.653	0.484	0.410	0.392

Notes: Correlations are based on administrative worker data at the individual level (see Section 4 for details). Correlations are calculated based on the mean skill in the 5-year period indicated in the column header. We define an occupational switch as a transition to an occupation different from the apprenticeship occupation (5-digit level). *Data source:* SIAB.

4. Data and Sample

To investigate the economic value of early-career skills, we link our skill measures to extensive labor market outcome data. More specifically, we analyze how cognitive, social, and digital skills conveyed through apprenticeship are associated with wages over workers' careers. To do so, we use administrative data of the German workforce providing panel information on labor market outcomes. We also employ additional cross-sectional survey data containing extensive information on worker characteristics to control more rigorously for selection into apprenticeships and for analyzing mechanisms.

4.1. Administrative Panel Data on Labor Market Outcomes (SIAB)

SIAB Data. The Sample of Integrated Labor Market Biographies (SIAB), provided by the Institute of Employment Research (IAB), is a 2% random sample of all workers in Germany subject to social security (Antoni et al., 2019; Frodermann et al., 2021) . These data are representative of the German workforce covered by social security legislation (i.e., excluding civil servants and self-employed).[24] Since employers are required by law to report the exact beginning and end of any employment relationship that is subject to social security contributions, SIAB is the largest and most reliable source of employment information in Germany. Moreover, misreporting of earnings is punishable by law, which

[24]SIAB also includes public-sector workers as long as they pay social security contributions (Antoni et al., 2019). Thus, the potential worry that selection into employment in the private sector varies over time (Edin et al., 2022) is no major concern in our data.

ensures high reliability of the earnings information. In addition to day-to-day information on earnings and employment status, SIAB also includes basic demographic characteristics, such as worker's age, gender, nationality, and education, as well as establishment characteristics (e.g., location, size, and industry). Initially, the SIAB data are structured in spells. To arrive at a yearly panel, we follow the procedure outlined in Dauth and Eppelsheimer (2020).

Linking Skill Measures to Outcome Data. Our apprenticeship skill data are measured at the 5-digit level, which is the most detailed occupational level that exists in Germany. Importantly, the SIAB data include information on an individual's apprenticeship occupation (and all subsequent occupations) also at the 5-digit level, allowing us to link skill data and outcome data at a very detailed level.[25] We use the occupational information from the last period of apprenticeship training observed in SIAB for merging our skill data to the outcome data. For almost half of our sample, we can observe this period directly. For the other half of the sample, we pursue two approaches to identify the last year of apprenticeship training (and the corresponding apprenticeship occupation) in SIAB. First, we use information on educational upgrading. We classify a period as the last year of apprenticeship training if an individual has no apprenticeship training in year $t-1$ and has completed apprenticeship training from year t onwards. Second, if an individual enters the sample with already completed apprenticeship training and has a labor market experience of below one year, we classify this period as the first after apprenticeship training and treat the worker's current occupation as her apprenticeship occupation. If a worker has completed multiple apprenticeships, we merge our skill data to the occupation observed upon completion of the first apprenticeship.[26]

Estimation Sample. From the 2% random sample of workers in SIAB, we focus on full-time workers with completed apprenticeship training. We exclude part-time employees from our analysis since we cannot observe daily hours worked in the SIAB data, rendering

[25] In some cases, different apprenticeship occupations exhibit the same 5-digit occupation code. For instance, the 2-year apprenticeship *Salesperson* and the 3-year apprenticeship *Management Assistant in Retail Business* share the same 5-digit code. In these cases, we use skill information from the larger apprenticeship (as measured by the number of new apprentices in 2017). This also means that we use the skill information of the more demanding apprenticeship (see e.g., Eggenberger et al., 2018). This leaves us with a total of 147 apprenticeship plans that we can merge to our outcome data.

[26] Note that the education variable in our administrative data always reports the highest attained degree (Fitzenberger et al., 2006). Thus, we cannot identify individuals as apprentices who obtained a university degree prior to their apprenticeship, since they appear in the data as university graduates.

the daily (part-time) wages of those workers less informative.[27] As we are interested in the returns to early-career skills over the life cycle, the sample includes workers whom we can follow over the first four consecutive 5-year periods after apprenticeship completion; i.e., an individual needs to have at least one non-missing wage observation in each of the four 5-year periods to be included in the sample. We do not restrict workers to be full-time employed for 15 or more years after labor market entry *without any interruption* to alleviate concerns about sample selectivity. We can also show that our sample restrictions do not systematically exclude workers with lower cognitive, social, or digital skills: On average, workers in our estimation sample acquire 13 months of cognitive skills, 4.6 months of social skills, and 2.1 months of digital skills (see Table 1); this is very similar in the sample of all trained workers, where workers learn 13 month of cognitive skills, 5.2 months of social skills, and 2.1 months of digital skills.[28]

Finally, we restrict our estimation sample to workers who have completed their apprenticeship after 1990, to reduce potential measurement error in our skill variables (recall that we derive skills from the most recent apprenticeship plan; see Section 3). Since we can observe workers until 2017 in the SIAB data, our sample consists of workers who finished their apprenticeship between 1990 and 2002, whom we follow for more than 15 years after labor market entry. This results in a sample of 66,432 workers.

4.2. Additional Data

Survey Data on Worker Skills and Characteristics (PIAAC). In addition to administrative labor market data, we also use survey data from the Programme for the International Assessment of Adult Competencies (PIAAC), conducted by the Organization for Economic Co-operation and Development (OECD). PIAAC provides test scores, labor market outcomes, and detailed background information for a representative sample of adults aged between 16 and 65 for a total of 37 countries (see OECD, 2013, for details). In Germany, respondents were surveyed in four waves between 2011/12 and 2016. In 2011/2012, test scores in the domains of numeracy, literacy, and problem-solving in technology-rich environments were assessed:

[27]As part of the social security reporting process, employers are required to provide information on the employment status of their employees, indicating whether they are employed on a part-time or full-time basis (Fitzenberger and Seidlitz, 2020).

[28]Two additional analyses, shown below, further address concerns about sample selectivity. First, the pattern of results is similar when we only require workers to have at least one full-time employment spell in a particular 5-year period after apprenticeship completion. Second, we show results separately for men and women, as one would expect that selection into full-time employment is stronger for women.

Numeracy: ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;

Literacy: ability to understand, evaluate, use, and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential;

Problem solving in technology-rich environments: ability to use digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks. For expositional purposes, we refer to this domain as "ICT skills" (see Falck et al., 2021).

Later waves elicited more detailed information on respondents' education and family background as well as on their non-cognitive skills. For the purpose of this paper, we focus on the 2011/2012 wave (providing wages, test scores, and job task information) and the 2014 wave (providing additional background information and non-cognitive skills).

In PIAAC, trained workers were asked in which occupation they completed their apprenticeship. We use this occupational information, which is available at the 5-digit level, to link our skill data to the survey data. The PIAAC estimation sample includes full-time workers with a completed apprenticeship. As the PIAAC data are purely cross-sectional, we cannot follow workers over their careers, so we pool all worker information after apprenticeship completion.

Online Job Vacancies (Lightcast). To investigate whether returns to early-career skills vary systematically by employers' demand for these skills, we rely on online job vacancies (OJV) provided by Lightcast, a labor market analytics firm that scrapes over 200 job boards and company websites in Germany. Lightcast removes duplicates and classifies the vacancies into standardized taxonomies, e.g., for occupations, regions, and industries. In addition, Lightcast maps keywords and phrases into distinct skill requirements. We can observe employers' skill demand at the county level from 2014 onwards. This leaves us with four years (2014-2017) in which we also have administrative worker data from SIAB. We can link a total of 18 million job ads.

We ensure direct comparability of workers' skills and employers' skill demand by assigning a corresponding apprenticeship skill label to each unique Lightcast skill. That is, we identify domain-specific skill demand based on the individual skill labels from the apprenticeship plans (instead of using information on the advertised occupation in an OJV). To arrive at regional skill demand intensities, we first code a binary indicator taking a value of one if a job ad specifies cognitive, social, or digital skills, and 0 otherwise.

Second, we compute the mean of these skill demand intensities by county over the years 2014-2017. We aggregate skill demand over all four years because we want to capture long-lasting regional differences in firms' production technology rather than year-to-year variation in skill demand (e.g., due to business cycle fluctuations). To facilitate interpretation, skill demand variables are standardized with mean zero and standard deviation one in our main estimation sample.

5. Estimation of Returns to Early-Career Skills

To understand how the skills provided through apprenticeship training are associated with workers' wages and wage growth over the life cycle, we estimate the following individual-level regression:

$$Y_{ijrty} = \alpha + \mathbf{Skills_j'}\beta_1 + \mathbf{Worker_{iy}'}\beta_2 + \mathbf{Apprenticeship_{jrt}'}\beta_3 + \varepsilon_{ijrty} \quad (1)$$

Y_{ijrty} is the outcome of interest for individual i who completed an apprenticeship in occupation j, county r, and year t measured $y \in \{$1-5, 6-10, 11-15, 16-20$\}$ years after apprenticeship completion. Our main outcome is log daily wages, but we also consider wage growth as additional outcome.[29] $Skills_j$ corresponds to the skills developed through an apprenticeship in occupation j, measured in months. We always include all skills to account for correlations between skills and to capture that occupations are represented by bundles of activities simultaneously requiring various skills to be carried out (Heckman and Scheinkman, 1987; Autor and Handel, 2013; Patt et al., 2021).

$Worker_{iy}$ is a vector of worker characteristics provided in the SIAB data, including gender, nationality, age fixed effects, and the educational degree obtained before starting an apprenticeship. In particular, age fixed effects control very flexibly for the relationship between age and earnings; the educational degree accounts for the fact that there are several pathways towards an apprenticeship. The vector $Apprenticeship_{jrt}$ includes a full set of fixed effects for the year of apprenticeship completion, which absorb unobserved effects that equally affect all workers who finish their apprenticeship in a given year (e.g., due to business cycles, changes in labor demand, or national policy changes). The completion year also captures cohort effects (i.e., over-time changes in worker characteristics which potentially coincide with the importance of certain skills). We also control for a full set of fixed effects for the county of the training establishment, which pick up regional differences in establishment performance, industry structure, and labor demand at a fine level.

[29] We use the average wage within a 5-year period, while missing wages are not treated as zeros.

The county effects also account for spatial differences in the distribution of skills (i.e., skill sorting), which may be related to returns to skills in the spirit of a Roy-type selection model (Roy, 1951). Finally, the inclusion of 1-digit apprenticeship occupation fixed effects controls for selection into an apprenticeship's broader occupational field (thus, we do not compare, say, carpenters with IT specialists).[30] ε_{ijrty} is an error term. We cluster standard errors at the level of the apprenticeship occupation.

In this framework, β_1 shows how the skills developed through an apprenticeship are associated with wages or wage growth, conditional on a rich set of control variables. We frequently refer to this estimate simply as the "return to skill".

The fact that we are not using any (quasi-)experimental variation in early-career skills precludes a causal interpretation of β_1. One particular concern is selection into apprenticeships. If more able or more diligent workers are also more likely to choose apprenticeships that provide, say, higher cognitive or digital skills, any positive relation between these skills and wages may just reflect worker ability or effort. To address these selection issues, we apply two strategies: First, we use extensive information in PIAAC to control for participants' educational history, family background, and non-cognitive skills. With regard to educational background, we observe a respondent's high school track and the final high school grades in math, German, and foreign language as a coarse measure of ability.[31] Variables for family background include the highest education level of mother and father in three categories (neither vocational nor university education, vocational education, university education) and the occupation of mother and father (2-digit level) when the respondent was 15 years old. These parental controls account for intergenerational persistence in both educational achievement and occupational choices. This is of particular importance in the case of Germany, which is struggling with high levels of inequality that persist across generations (OECD, 2018). Non-cognitive skills assessed in PIAAC include the Big Five (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) and grit (see Almlund et al., 2011, for a comprehensive discussion of the importance of non-cognitive skills for labor market success).[32]

[30]The estimated returns to skills when controlling for occupational fields likely understate the full economic value of skills, because variation in skills or wages between occupational fields is neglected.

[31]Maurer et al. (2023) show that students' high school GPA is a good proxy for students' academic ability in Germany.

[32]PIAAC regressions include all apprenticeship skills and additionally control for basic worker characteristics (i.e., gender, migrant status, quadratic polynomial in age, and highest pre-apprenticeship educational degree). Due to the cross-sectional nature of the PIAAC data, we only have one wage observation per individual coming from different points in individuals' careers. The addition of a quadratic polynomial in age controls flexibly for the evolution of wages over the life cycle. Moreover, a small share

Second, we control even more rigorously for characteristics of the establishment in which a worker completed the apprenticeship. Our administrative data include information on size (number of full-time employees), age, and industry of the establishment.[33] We also control directly for establishment productivity, measured as the proportional wage premium (or discount) that is paid by an establishment to all workers. These productivity measures are the establishment fixed effects in a regression of worker wages on time-varying worker and establishment characteristics, worker fixed effects, and establishment fixed effects, estimated for various periods in the universe of workers subject to social security contributions in Germany (see Bellmann et al., 2020, for details). This estimation follows the two-way fixed effects model of Abowd et al. (1999) and thus the establishment effects are referred to as "AKM effects". We control for the AKM effects in a continuous fashion to account for a potential selection of individuals into more productive apprenticeship establishments. However, AKM effects are not available for all establishments and all years, thus our SIAB sample reduces to 51,612 workers in the AKM models. Finally, to control for selection even more rigorously, we estimate specifications with apprenticeship establishment fixed effects. That is, we compare the wage development of workers who complete their apprenticeship in the same establishment, year, and occupational group, but in different (detailed) apprenticeship occupations. In this very demanding specification, the effective number of observations reduces to 23,893 workers with within-establishment and within-completion-year variation in skills.

6. Returns to Early-Career Skills

In this section, we investigate how workers with different skills acquired during apprenticeship fare on the labor market over the life cycle.

6.1. Wages

We begin with an analysis to determine whether a worker's acquired skills during apprenticeship are related to wages throughout the career. Table 5 reports results of a regression of wages in several periods after apprenticeship completion on cognitive, social,

of respondents did not report the final high school grade in math or German (each about 2% of the sample), while the share of missings for the grade in foreign language is larger (about 12% of the sample). To avoid losing these observations, we imputed values for missing grade variables. To ensure that the imputed data are not driving our results, all regressions with the PIAAC data include an indicator for each variable with missing data that equals 1 for imputed values and 0 otherwise.

[33] Arellano-Bover (2022) shows that starting the career in a larger firm improves workers' long-term labor market prospects.

and digital skills. We focus on workers with at least one wage observation in the first four consecutive 5-year periods after finishing the apprenticeship, so the estimated wage returns reflect wage changes of the same individuals over their careers. All regressions include a full set of controls for worker and apprenticeship characteristics. All other apprenticeship skills (manual, management, and admin) are also included to account for correlations between the skills.

Table 5: Wage Returns to Early-Career Skills

	Log daily wages after			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Cognitive skills (months)	0.008	0.010**	0.011**	0.013***
	(0.0050)	(0.0045)	(0.0044)	(0.0042)
Social skills (months)	0.007	0.013**	0.016***	0.015***
	(0.0055)	(0.0053)	(0.0051)	(0.0049)
Digital skills (months)	–0.004	0.010	0.017**	0.021***
	(0.0056)	(0.0065)	(0.0077)	(0.0080)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
F-statistic (all skills)	1.7	4.9	7.0	8.1
N (individuals)	66,432	66,432	66,432	66,432

Notes: Sample consists of workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data source:* SIAB.

Table 5 shows that workers who start their career with higher cognitive skills earn significantly higher wages over subsequent years. This is true over time horizons as long as 20 years, regardless of their future job transitions. For example, one additional month of learning cognitive skills (corresponding to the skill distance from a paper technologist (17.3 months) to a digital and print media clerk (18.3 months)) during apprenticeship is associated with 1.3% higher wages 16-20 years later. In terms of magnitude, returns to one month of cognitive skills amount to 10-16% of the return to a full year of schooling, depending on the position in the career, which indicates that these returns are also economically relevant.[34] Only in the first five years in the labor market are cognitive skills not significantly related to wages. The same is true for social and digital skills, potentially suggesting that there is no meaningful selection into apprenticeships that provide more cognitive, social, or digital skills. If such a selection pattern was present, one would expect to find positive returns to skills throughout the career, as unobserved confounds systematically related to skills would drive up wages. However, it may also be that there is selection based on expected lifetime earnings rather than entry wages, or that selection effects only materialize later in a career because variation in wages across workers grows over time. Thus, we provide a more rigorous analysis of selection in Section 8.

Returns to social and digital skills over the career are even larger than returns to cognitive skills. 16-20 years after apprenticeship completion, one additional month of learning social skills (e.g., corresponding to the skill distance between an office management clerk (7.03 months) and an e-commerce salesperson (8.13 months)) is associated with 1.5% higher wages, while one additional month of learning digital skills (e.g., corresponding to the skill distance from a media designer (8.25 months) to an IT management assistant (9.45 months)) even pays 2.1% higher wages. These returns amount to 19% (social skills) or even 27% (digital skills) of the return to an additional year of schooling, emphasizing the economic value of social and digital skills.[35] Returns to social and digital skills also increase particularly fast for early-career workers.[36]

The results in Table 5 are based on workers with at least one full-time employment spell in each of the first four 5-year periods after apprenticeship completion. Due to this

[34]We estimate returns to schooling in a pooled sample of apprenticeship graduates working full time in the SIAB data. Worker and apprenticeship controls from Equation 1 (except for pre-apprenticeship education) are also included. The return to one year of schooling amounts to 7.9% in this specification.

[35]Manual, management, or administrative skills are not significantly related to wages in any of the 5-year periods after labor market entry (Table B.1). While estimated returns to manual and administrative skills are always close to zero, returns to management skills are sizable, but imprecisely estimated.

[36]Note that increases in the returns to skills over the career may also partly reflect that earnings later in the career are a better proxy for lifetime earnings (see Hanushek et al., 2015, for a discussion).

restriction, our sample consists of workers without longer unemployment or part-time spells early in the career. Moreover, when imposing that we have to be able to follow workers over more than 15 years, we ignore the labor market experiences of workers who entered the labor market towards the end of our observation period. Thus, we also show results when including all full-time workers with at least one wage observation in a given 5-year period after apprenticeship completion (Table B.2). We find that returns to skills tend to increase in this more encompassing sample. However, these results not only reflect wage changes of the same workers over their careers, but also compositional changes.

Table B.3 shows the results by gender. Intriguingly, returns to skills differ between men and women. Returns to cognitive and social skills tend to be higher for women than for men. The social skills result in line with the argument that differences in soft skills may partially explain why labor market outcomes have been improving for women relative to those for men (Autor and Wassermann, 2013; Beaudry and Lewis, 2014). In contrast, digital skill are highly rewarded for men, while returns to digital skills are not significant for women (despite sizable point estimates). Moreover, returns to skills increase over the career for men, but remain rather stable for women. These gender differences in returns to skills clearly warrant further investigation, which is however beyond the scope of this paper.

6.2. Wage Growth

We now turn to an analysis of the behavior of wage changes. In Table 6, we consider wage growth over the first 20 years of workers' careers. Following Cortes (2016), we calculate individual wage growth between the first 5-year period after labor market entry and each of the three later periods. Higher cognitive skills are related to modest wage growth at best. In contrast, the wage growth associated with higher social and – in particular – digital skills is much more pronounced. For instance, relative to their wages in the first five years after apprenticeship completion, wages of workers who acquired one additional month of digital skills grow faster annually by 0.24 percentage points in the five years thereafter; 11-15 years and 16-20 years, respectively, after apprenticeship completion, wage growth amounts to 0.19 and 0.16 percentage points.[37]

Taken together, the results in this section show that early-career workers benefit from higher cognitive, social, and digital skills by earning higher wages and experiencing faster wage growth over the life cycle. In Appendix C, we investigate channels through which

[37]This fast wage growth for digital-intense workers is also driven by the fact that these workers do not experience any wage advantage immediately after labor market entry.

Table 6: Early-Career Skills and Wage Trajectories

	Wage growth relative to initial period (× 100)		
	6–10 yrs	11–15 yrs	16–20 yrs
	(1)	(2)	(3)
Cognitive skills (months)	0.026	0.025	0.029*
	(0.0214)	(0.0192)	(0.0163)
Social skills (months)	0.104***	0.085***	0.054***
	(0.0172)	(0.0154)	(0.0136)
Digital skills (months)	0.243***	0.193***	0.160***
	(0.0333)	(0.0316)	(0.0261)
All skills	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes
Apprenticeship controls			
Completion year FE	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes
Outcome mean	2.05	1.47	1.17
F-statistic (all skills)	18.57	14.05	10.29
N (individuals)	66,432	66,432	66,432

Notes: Sample consists of full-time workers with completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is the average annual growth rate of wages (multiplied by 100) between the first five years after apprenticeship completion and the period indicated in the column header (e.g., Column 1 corresponds to the growth between the average wage in the years 1-5 after apprenticeship completion and the average wage in the years 6-10). Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (gender, nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

these returns materialize. We find that human capital investments, specifically educational upgrading (Table C.1) and on-the-job training (Table C.2), as well as occupational switching are mechanisms explaining returns to skills.

7. Drivers of Returns to Early-Career Skills

The goal of this section is to understand what influences returns to skills. In particular, do workers who acquire specific types of skills simultaneously in their apprenticeship earn higher wages? If so, between which skills do such complementarities exist? We also examine whether differences in the regional demand for skills are associated with changes in returns to these skills. Finally, we show that our returns-to-skills estimates do not simply reflect returns to occupations.

7.1. Skill Complementarities

We find evidence for a skill complementarity between cognitive and social skills, consistent with Weinberger (2014), Deming and Kahn (2018), and Kiener et al. (2023). Table 7 shows that workers who completed an apprenticeship providing both higher cognitive and social skills are particularly valuable on the labor market.[38] The strength of this cognitive social skill complementarity changes only little as workers progress in their careers. One interpretation of this finding is that worker who possess both cognitive and social skills can perform more complex functions at the job, increasing their productivity (see Deming and Kahn, 2018, for a similar argument).

Perhaps surprisingly, we find that simultaneously acquiring more cognitive and digital skills or more social and digital skills during apprenticeship does not generate a wage advantage. In fact, the interaction between cognitive and digital skills is negative and significant, indicating that these skills are partly substitutable. One explanation for this result is that some of the skills we assigned to the "cognitive" domain, such as math and statistics (see Table 2), are also required in digital-intense jobs.

7.2. Regional Skill Demand

We also investigate whether wage returns to early-career skills systematically vary with firms' production technologies, reflected in their skill demand in online job ads.[39] To do so, we obtained OJV data from Lightcast for the period 2014-2017, using the skill identifiers

[38]To facilitate interpretation, all skill variables in the interacted models are de-meaned.

[39]We follow Deming and Kahn (2018) in interpreting the stated preferences of firms in the posted job vacancies as a proxy for firms' production technology.

Table 7: Wage Returns to Early-Career Skills: Interacted Model

	Log daily wages after			
	1–5 yrs	6–10 yrs	11–15 yrs	16–20 yrs
	(1)	(2)	(3)	(4)
Cognitive skills (months)	0.012***	0.012***	0.012***	0.014***
	(0.0043)	(0.0039)	(0.0040)	(0.0040)
Social skills (months)	0.012**	0.015***	0.016***	0.015***
	(0.0056)	(0.0055)	(0.0057)	(0.0055)
Digital skills (months)	–0.004	0.010*	0.018***	0.022***
	(0.0051)	(0.0057)	(0.0064)	(0.0069)
Cognitive × social	0.003***	0.002***	0.002**	0.002**
	(0.0008)	(0.0009)	(0.0009)	(0.0010)
Cognitive × digital	–0.002*	–0.002**	–0.002**	–0.002**
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Social × digital	–0.004	–0.003	–0.003	–0.004
	(0.0028)	(0.0030)	(0.0033)	(0.0033)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
N (individuals)	66,432	66,432	66,432	66,432

Notes: Sample consists of workers with completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months; all skill measures are de-meaned. We control for the other skill groups (manual, management, admin) and worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data source:* SIAB.

from the apprenticeship plans to classify skills in the OJV data (see Section 4.2 for a description of the data and creation of our regional skill demand measure). Separately for cognitive skills, social skills, and digital skills, we interact the respective skill measure with the regional demand for these skills in OJVs. We ask whether a certain skill pays higher returns in counties in which firm technology is such that the job likely requires the skills that individuals have learnt in their apprenticeship. We also ask whether a certain skill, say, cognitive, pays higher returns in counties in which firm technology is such that the job likely requires additional skills, i.e., social or digital skills.

Results of the interactions of firms' skill demand with workers' cognitive skills are presented in Table 8. In Columns 1-3, we include our baseline controls and add county-of-residence fixed effects (i.e., the level at which the OJV data are merged with the worker data) and year fixed effects. In Columns 4-6, we additionally include fixed effects for the 5-digit apprenticeship occupation (i.e., the level at which our apprenticeship skill measures vary). In these models, the interactions between workers' skills and firms' skill demand are identified from variation in skills across counties, so any confounding variables that affect skills and wages similarly across counties are accounted for.[40] Two findings from this interacted model stand out. First, cognitive skills learnt during apprenticeship pay higher returns in counties in which firm technology likely requires such skills. In Column 1, returns to one additional month of acquiring cognitive skills increases by 0.2% when the regional demand for cognitive skills is one standard deviation higher. Second, returns to cognitive skills also increase in regions where firms have higher demand for digital skills, suggesting that workers with higher cognitive skills are particularly valuable for cognitive-intense *and* digital-intense firms. This is in line with the previous argument that cognitive and digital skills are imperfect substitutes for firms.[41]

The result that workers who acquired more of a specific skill during apprenticeship earn more in firms that supposedly use this skill more intensely in production suggests that our skill measures indeed capture differences in workers' (skill-specific) productivity and do not simply pick up general wage differences across apprenticeship occupations. We turn to this issue in more detail in the next section.

[40] Note that the main effects of the skill demand variables are not identified because they have no time variation and are thus perfectly collinear to the county fixed effects. Analogously, the main effects of workers' skills are not identified in the specifications with 5-digit occupation fixed effects (Columns 4-6).

[41] In unreported regressions, we also interact social or digital skills with the skill demand variables. Returns to social skills do not vary with firms' skill demand. For digital skills, we observe a sizeable interaction with cognitive skill demand, which is, however, imprecisely estimated. The observation that returns to social and digital skills are not systematically higher in firms that have a more cognitive-intense or digital-intense production technology suggests that these firms do not just generally pay better.

Table 8: Wage Returns to Cognitive Skills: Interactions with Firms' Skill Demand from Job Vacancy Data

	Log daily wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive skills (months)	0.016***	0.016***	0.016***			
	(0.0041)	(0.0041)	(0.0041)			
× Cognitive skill demand	0.002***			0.001***		
	(0.0006)			(0.0005)		
× Social skill demand		–0.000			–0.000	
		(0.0004)			(0.0003)	
× Digital skill demand			0.001**			0.001*
			(0.0006)			(0.0005)
All skills	Yes	Yes	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Apprenticeship controls						
Completion year FE	Yes	Yes	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	No	No	No
Occupation FE (5-digit)	No	No	No	Yes	Yes	Yes
N (individuals × years)	721,508	721,508	721,508	721,508	721,508	721,508

Notes: Sample consists of full-time workers with a completed apprenticeship training. We only include data for the years 2014 to 2017 to ensure a direct overlap of our apprenticeship skill data with OJV data. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is log daily wages. Early-career skills are measured in months and are de-meaned to facilitate interpretation. Skill demand is measured as the share of job ads in a county that requests a specific skill, standardized with mean zero and standard deviation one (see Section 4.2). We control for the other skill groups (manual, management, admin) and worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* SIAB and Lightcast.

7.3. Returns to Occupations or Returns to Skills?

Since we derive our skill measures from apprenticeship plans, we only observe worker skills at the occupational level. Despite controlling for occupational fields in our wage regressions, one may be worried that our returns-to-skills estimates reflect wage differences across specific apprenticeship occupations rather than returns to actual worker skills. To address this concern, we resort to the PIAAC data, in which we observe actual worker skills and the content of their jobs at the individual level (see Section 4.2).

Correlation of Early-Career Skills with PIAAC Test Scores. Table D.1 shows that individuals who completed apprenticeships that were more intense in cognitive, social, or digital skills also have higher test scores in the respective domain later in their careers. First, cognitive, social, and digital skills obtained through apprenticeship training are significantly positively correlated with numeracy and literacy skills tested in PIAAC. The relationship is strongest for digital skills: A one-month increase in digital skills is associated with an increase in test scores by 0.032 standard deviations in numeracy and 0.030 standard deviations in literacy. These associations are also economically meaningful, as they amount to 16% (numeracy) or 18% (literacy) of the skill increase for an entire year of schooling.[42] Thus, individuals who have completed apprenticeships in more cognitive-, social- or digital-skill-intense occupations also have higher numeracy and literacy skills at the individual level, which may partly explain the estimated skill returns to early-career skills.[43]

While numeracy and literacy skills in PIAAC are rather general information-processing competencies, ICT skills are more specific and closely related to digital competencies. Reassuringly, individuals who completed a more digital-intense apprenticeship also score significantly higher in PIAAC's ICT skills assessment (Column 3 of Table D.1). The magnitude of this association is also considerable: The ICT skills increase of one additional month of acquiring digital skills during apprenticeship amounts to 18.5% of the ICT skill increase due to an entire year of schooling. At the same time, the cognitive- or social-skill content of apprenticeships does not predict differences in ICT skills at the individual level. This is evidence for a domain-specific mapping of apprenticeship skills to individual-level

[42] Replacing apprenticeship skills by years of schooling in the PIAAC regressions (without controlling for pre-apprenticeship education), the estimated schooling coefficients are 0.203 for numeracy, 0.179 for literacy, and 0.168 for ICT skills.

[43] Hanushek et al. (2015, 2017) show that PIAAC skills are significantly related to higher wages and better employment prospects in Germany and internationally.

skills, which is at odds with the idea that the observed returns to apprenticeship skills simply reflect returns to occupations.

Correlation of Early-Career Skills with PIAAC Task Use on the Job. Next, we show that skills formed through apprenticeship training not only predict (domain-specific) test scores, but also (domain-specific) job tasks later in the career. For this analysis, we make use of the detailed questions in PIAAC on how often respondents perform certain tasks at their job. Based on these questions, we construct six variables reflecting various dimensions of the task content of individuals' workplace: Numeracy task use (simple and advanced), social task use, experience with computers, computer use, and internet use. With the exception of computer experience at the job, which is a binary indicator, all variables are indices that combine multiple items from the PIAAC questionnaire. Following the approach by Kling et al. (2007), indices are constructed as an equally weighted average of the z-scores of the included items, which is standardized with standard deviation 1.

Table D.2 reports how early-career skills are related to the task use indices at the current job. Individuals with higher cognitive skills tend to perform more simple numeracy tasks, such as calculating costs or budgets and preparing charts, graphs, or tables (Column 1); however, the association is not statistically significant. Advanced numeracy tasks, e.g., using algebra or advanced math, is significantly associated with digital skills (Column 2). Intriguingly, we find evidence for a domain-specific mapping of early-career skills to current workplace tasks. First, workers who acquired more social skills during apprenticeship also perform more social tasks at their current job, which involve advising others, influencing others, negotiating with others, and sales activities (Column 3). Neither cognitive nor digital skills are related to social task use. Second, workers with higher digital skills – but not those with higher cognitive or social skills – are significantly more likely to use a computer at the workplace and, conditional on using a computer, perform more computer-related activities (Columns 4 and 5). Unsurprisingly, none of the skill measures is associated with higher internet use on the job (again conditional on using a computer) (Column 6), as the internet has become an essential tool in a wide variety of occupations, regardless of the level of skills required for the job.

Our results show that higher early-career skills do not mechanically lead to more tasks being performed at the current job. Rather, the association is domain-specific. This provides further confidence that trained workers learn the skills outlined in the apprenticeship plans and apply them later in their jobs. These results also support the idea that the estimated skill-wage associations do not simply reflect returns to occupations, but returns to skills actually learned during apprenticeship training (and used later in the job).[44]

8. Selection

In this section, we provide evidence that the positive association of early-career skills with wages is not driven by selection into apprenticeships. First, we show that our results also hold when conditioning on a large set of additional controls for ability, family background, and non-cognitive skills. Since our administrative worker data do not contain such information, we perform the analysis with the cross-sectional PIAAC data (see Section 4.2).[45] Column 1 of Table D.3 shows that we can replicate our results from the administrative worker data with PIAAC. Without further background controls, we find that one additional month of learning cognitive skills during apprenticeship is associated with a wage increase of 2.1%. The wage increase for social skills is even larger at 2.9%, while returns to digital skills are 1.4%, just shy of statistical significance (p=0.124). In the remainder of Table D.3, we sequentially add final high school grades in math, German, and foreign language (Column 2), parental education and occupation (Column 3), and non-cognitive skills (Column 4). Intriguingly, estimated returns to skills are hardly affected by the inclusion of these additional controls, and returns to digital skills even reach statistical significance at conventional levels. This suggests that our baseline set of controls for worker background and apprenticeship characteristics already accounts for the most daunting confounds.

[44] A more direct test of whether the estimated returns to early-career skills indeed reflect wage premia of skills learnt during apprenticeship would be to compare returns to skills between trained workers and, say, university graduates working in the same occupation without apprenticeship training. If trained workers would earn higher rewards for their skills than better-educated workers without apprenticeship training, this would be strong evidence for the existence of returns to skills. However, such test would require a rather balanced share of trained workers and university graduates in an apprenticeship occupation. In reality, the share of university graduates in apprenticeship occupations is extremely low (only 2% in our sample), suggesting that such occupations are either not attractive for university graduates or that firms prefer workers who are specifically trained for the respective occupation. Since university graduates in apprenticeship occupations are likely a highly selective group of workers, we refrain from analyzing them further.

[45] Earlier work by Hanushek et al. (2015) finds that estimated returns to skills in PIAAC are sensitive to position in the career, as it may take time for firms to learn about relevant differences among workers (e.g., Altonji and Pierret, 2001) and due to early-career job-skill mismatch (e.g., Jovanovic, 1979). Thus, following Hanushek et al. (2015), we restrict the PIAAC sample to full-time workers aged 35 and above, to focus on more stable employment relationships. We report results for hourly wages, where the bottom and top 1% of the wage distribution are trimmed to limit the influence of outliers.

Another worry is that unobserved worker characteristics are systematically related to the type of apprenticeship establishment workers sort into. For instance, it may be that higher ability workers are also more likely to sort into successful, more productive establishments that pay higher wages irrespective of the skills provided through the apprenticeship. Similarly, bigger or older establishments may be more likely to offer certain types of apprenticeships and also pay higher wages. Thus, estimated returns to early-career skills may actually represent returns to working in certain types if establishments. To address such concerns, we add establishment age, size, and industry at the time of apprenticeship completion as additional controls to our main specification. Furthermore, we include a proxy for an establishment's productivity, measured by establishment (AKM) effects (see Section 5). Estimated returns to skills are robust to adding these establishment-level controls (Table 9, even columns). For cognitive and social skills, estimated returns reduce to roughly half the size of the baseline specification (shown in the odd columns) in this rigorous model. Yet, estimated returns to digital skills even increase compared to our baseline specification. This result can be explained by the fact that workers with higher digital skills are more likely to work in lower-paying industries, driving down their wages when industry differences are not accounted for.[46] However, the basic pattern of estimated returns to digital skills over the career is little affected by the inclusion of the additional establishment controls.[47]

In Table 10, we control even more rigorously for selection by including apprenticeship establishment fixed effects. Thus, we compare workers in different apprenticeship occupations who graduate from the same establishment, in the same year, and in the same occupational group. Since returns in this specification are identified from within-establishment, within-year, and within-occupational variation in early-career skills, the sample size reduces considerably compared to our main analysis. However, even in this very restrictive specification, returns to cognitive and digital skills remain positive and significant in most periods (even columns). In fact, the return estimates change only little in magnitude compared to the baseline model (odd columns) and its precision even increases when exploiting only the narrow within-establishment variation. However, returns

[46]The correlations of digital skills with establishment size, age, and productivity (which themselves are positively related to wages) are all positive, but modest in size.

[47]Another way to account for worker sorting by establishment size is to estimate returns to skills separately for workers who completed their apprenticeship in establishments of different sizes. Using the median number of full-time employees as size cutoff, we find that returns to skills are qualitatively similar for workers trained in either small or large establishments (Table B.4). However, returns to cognitive and digital skills tend to be somewhat higher for workers coming from small establishments.

to social skills, while similar in magnitude as returns to cognitive skills, are less precisely estimated.

Evidence from these additional robustness analyses indicates that our returns-to-skills estimates are unlikely to be driven by confounding variables.

Table 9: Wage Returns to Early-Career Skills: Controlling for Establishment Characteristics

	Log daily wages after							
	1–5 yrs	1–5 yrs	6–10 yrs	6–10 yrs	11–15 yrs	11–15 yrs	16–20 yrs	16–20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive skills (months)	0.009*	0.003*	0.012**	0.005***	0.013***	0.006***	0.014***	0.008***
	(0.0052)	(0.0018)	(0.0047)	(0.0018)	(0.0045)	(0.0020)	(0.0045)	(0.0025)
Social skills (months)	0.008	0.003	0.014***	0.008**	0.018***	0.010**	0.018***	0.009**
	(0.0055)	(0.0029)	(0.0051)	(0.0036)	(0.0051)	(0.0040)	(0.0049)	(0.0044)
Digital skills (months)	–0.007	0.001	0.008	0.015***	0.015**	0.022***	0.021***	0.028***
	(0.0057)	(0.0035)	(0.0064)	(0.0040)	(0.0073)	(0.0047)	(0.0076)	(0.0057)
All skills	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Apprenticeship controls								
Completion year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of full-time employees	No	Yes	No	Yes	No	Yes	No	Yes
Establishment age	No	Yes	No	Yes	No	Yes	No	Yes
Establishment industry (3-digit)	No	Yes	No	Yes	No	Yes	No	Yes
AKM Effects	No	Yes	No	Yes	No	Yes	No	Yes
F-statistic (all skills)	2.3	4.9	5.2	7.4	7.7	10.9	8.6	8.4
N (individuals)	51,612	51,612	51,612	51,612	51,612	51,612	51,612	51,612

Notes: Sample consists of workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Columns 1 and 2 correspond to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls include year of completion, county of training establishment, and occupational field (1-digit). In the even columns, we add the following additional apprenticeship establishment controls: Number of full-time employees, age, industry (3-digit), and productivity (measured by AKM effects). All establishment controls are measured at the year of completing the apprenticeship. Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Table 10: Wage Returns to Early-Career Skills: Controlling for Establishment Fixed Effects

	Log daily wages after							
	1–5 yrs (1)	1–5 yrs (2)	6–10 yrs (3)	6–10 yrs (4)	11–15 yrs (5)	11–15 yrs (6)	16–20 yrs (7)	16–20 yrs (8)
Cognitive skills (months)	0.004	0.002	0.005	0.005**	0.006	0.005**	0.008**	0.007**
	(0.0037)	(0.0021)	(0.0036)	(0.0022)	(0.0039)	(0.0024)	(0.0037)	(0.0029)
Social skills (months)	0.007**	0.003	0.010***	0.004	0.011***	0.006	0.011***	0.005
	(0.0033)	(0.0041)	(0.0034)	(0.0038)	(0.0038)	(0.0041)	(0.0038)	(0.0055)
Digital skills (months)	0.001	0.004	0.014**	0.012***	0.020***	0.015***	0.022***	0.018***
	(0.0039)	(0.0031)	(0.0058)	(0.0043)	(0.0069)	(0.0048)	(0.0073)	(0.0051)
All skills	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Apprenticeship controls								
Completion year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of establishment FE	Yes	No	Yes	No	Yes	No	Yes	No
Occupation FE (1-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	No	Yes	No	Yes	No	Yes	No	Yes
F-statistic (all skills)	1.3	8.2	3.3	5.8	5.3	5.1	6.4	5.8
N (individuals)	23,893	23,893	23,893	23,893	23,893	23,893	23,893	23,893

Notes: Sample consists of workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Columns 1 and 2 correspond to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, occupational field (1-digit). In the even columns, we control for apprenticeship establishment fixed effects. Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data source:* SIAB.

9. Returns to Skills over Time

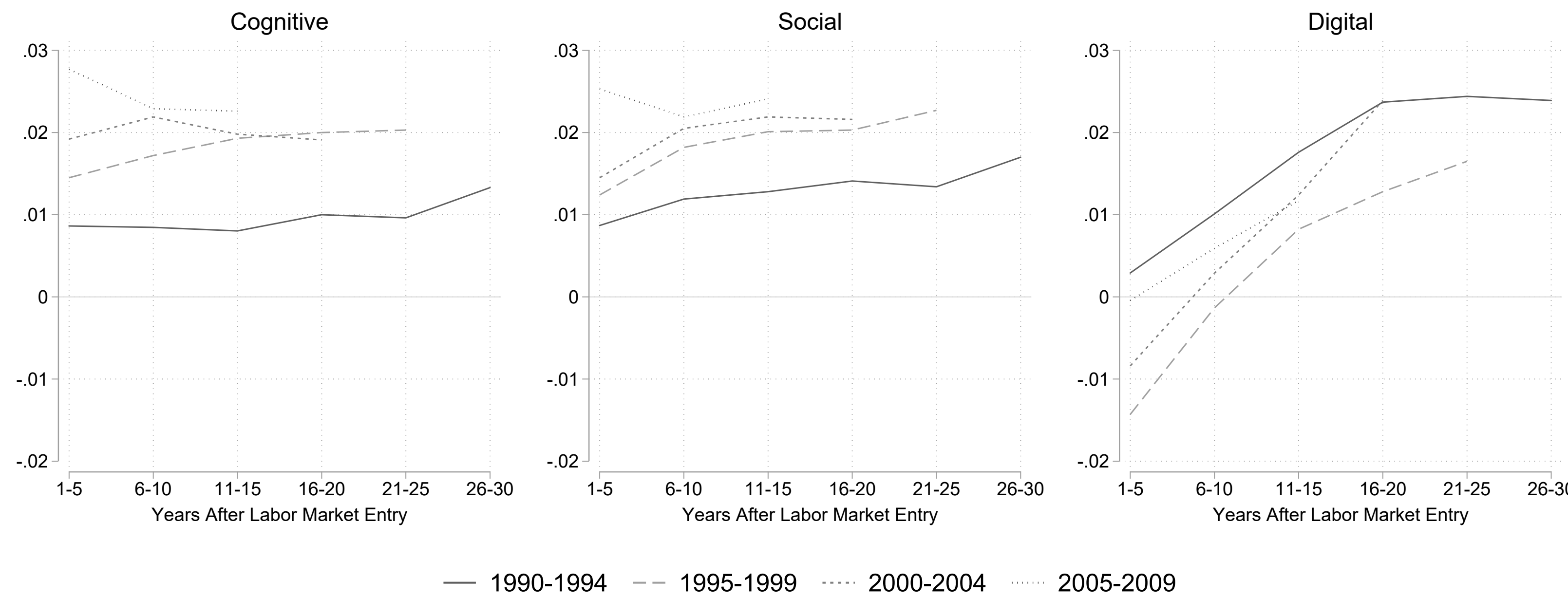
In this section, we investigate how returns to skills have evolved over time. We first estimate returns over the life cycle for different entry cohorts. Then, we directly assess how returns to skills have changed over time by providing annual return estimates in a sample of prime-aged workers. Our rich administrative data allow us to estimate returns to skills over almost three decades.

9.1. Following Different Cohorts over their Careers

To develop a more complete understanding of how returns to skills have evolved over time, we follow cohorts of trained workers who have entered the labor market at different points in time over their careers. More specifically, we estimate the model in Equation 1 by entry cohort and for different bins of potential labor market experience, ranging from 1 to a maximum of 30 years after apprenticeship completion (depending on the entry cohort). These estimates not only show how returns to skills change as workers gain labor market experience, they also provide insights how the returns have evolved over time by comparing different entry cohorts. Figure 2 presents returns-to-skills estimates for four different entry cohorts. We bunch cohorts into 5-year periods, so the first cohort entered the labor market after apprenticeship completion in the years 1990-1994 and the last cohort in the years 2005-2009. For cognitive skills, we observe that workers who more recently entered the labor market started their careers with higher returns. For instance, average returns to cognitive skills during the first five years on the labor market amounted to 0.9% for workers who entered the labor market between 1990 and 1994; these initial returns increased to 1.5%, 1.9% and even 2.8% for the entry cohorts 1995-1999, 2000-2004, and 2005-2009, respectively. Moreover, all cohorts witnessed only modest, if any, return increases throughout the career. For instance, even after 26-30 years on the labor market, workers from the entry cohort 1990-1994 had returns of just 1.3%. This slow-growth pattern in the returns to cognitive skills mimics our results in Table 6.

For social skills, we observe a very similar rise in initial returns by entry cohort as for cognitive skills; returns to social skills increased from 0.9% in the 1990-1994 entry cohort to 2.5% in the 2005-2009 entry cohort. However, returns to social skills have increased faster with experience than returns to cognitive skills in all cohorts.

Figure 2: Wage Returns to Cognitive, Social, and Digital Skills by Potential Experience and Cohort



Notes: Sample consists of individuals with a completed apprenticeship training who work full-time in a given year. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. The dependent variable is log daily wages. Returns to skills are estimated separately for each labor market entry cohort indicated in the graph by potential experience bin. Potential experience is defined as the number of years elapsed since a worker finished her apprenticeship. Early-career skills are measured in months of learning the respective skill during the apprenticeship. Estimated returns are conditional on the other skill domains (manual, management, admin), worker characteristics (gender, nationality, age fixed effects, and pre-apprenticeship educational degree), and apprenticeship characteristics (year of completion, county of training establishment, and occupational field (1-digit)). *Data source:* SIAB.

The most striking pattern emerges for digital skills. Workers with higher digital skills experienced a far stronger increase in wages over their careers than workers with higher cognitive or social skills; at the same time, returns to digital skills were also much lower at labor market entry (sometimes even negative). Intriguingly, the cohort that entered the labor market between 1990 and 1994, when computers started to become more widespread in the economy, witnessed comparatively high returns to digital skills at labor market entry that also increased quickly during the career. Due to this rapid growth, returns to digital skills have caught up with or even surpassed the returns to cognitive and social skills by the end of our observation period (with the exception of the most recent cohort).

It is important to note that lower returns for the earlier cohorts may partly be due to higher measurement error in the skills of these cohorts, since we assign all workers the most recent apprenticeship plan (see Section 3). However, this skill measurement does not affect the within-cohort comparisons over the career. Moreover, it is not systematically the case that earlier worker cohorts earn lower returns, suggesting that the patterns in Figure 2 are not just driven by differential measurement error but indeed reflect changes in returns to skills over time.

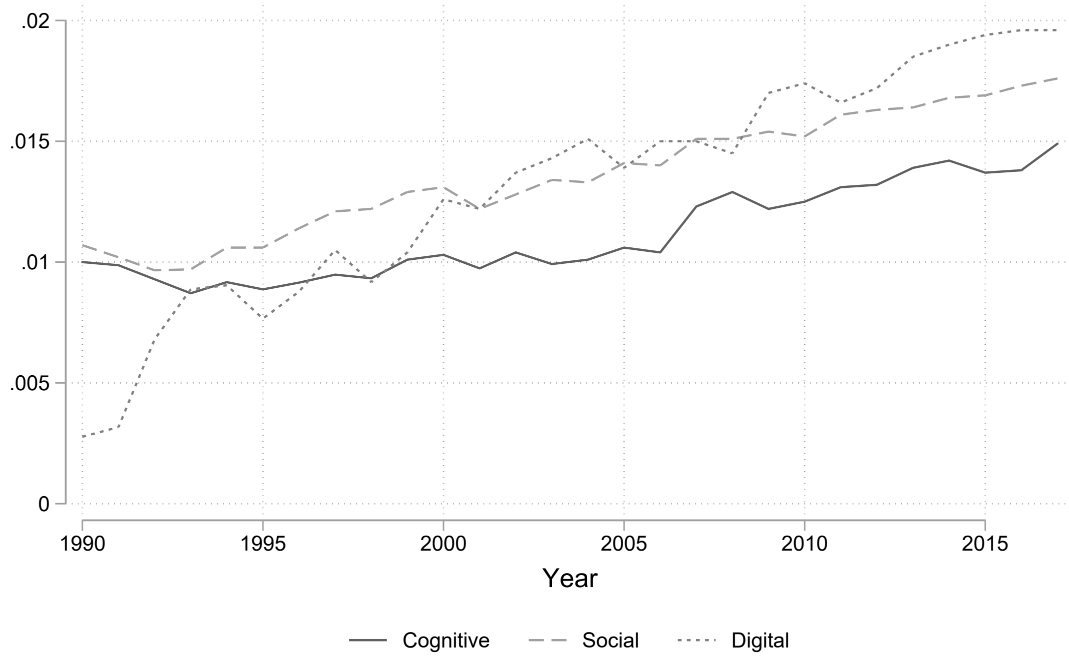
9.2. Returns by Year

An alternative way to see the evolution of returns to skills is to estimate returns annually for the same age cohort. We show returns estimates in a sample of prime-aged workers, whose current earnings provide a good proxy for lifetime earnings (Haider and Solon, 2006; Boehlmark and Lindquist, 2006).[48] Figure 3 plots the returns to cognitive, social, and digital skills from estimating the model in Equation 1 by year for the period 1990 to 2017. The figure displays a strong increase in the wage returns to all three skill domains over the last three decades. Mimicking the pattern in Figure 2, returns to cognitive skills experienced the slowest growth. Returns to social skills were at about the same level as returns to cognitive skills in 1990, but were about 20% larger than the cognitive-skill returns by the end of our observation period. Returns to digital skills were very modest in 1990, but started to increase markedly when the computer revolution began to take off in the 1990s. By 2017, returns to digital skills did increase by a factor of 7 compared to the 1990 value.

In sum, our analysis shows that the labor market value of cognitive, social, and digital skills of low- and medium-educated workers has strongly increased over the last three

[48]See Edin et al. (2022) for a similar approach with Swedish data.

Figure 3: Wage Returns to Cognitive, Social, and Digital Skills, 1990-2017



Notes: Sample consists of full-time workers with a completed apprenticeship training aged 35-54 years in a given year. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. The dependent variable is log daily wages. Returns to skills are estimated separately for each year and the respective coefficients for cognitive, social, and digital skills are shown. Early-career skills are measured in months of learning the respective skill during the apprenticeship. Estimated returns are conditional on the other skill domains (manual, management, admin), worker characteristics (gender, nationality, age fixed effects, and pre-apprenticeship educational degree), and apprenticeship characteristics (year of completion, county of training establishment, and occupational field (1-digit)). *Data source:* SIAB.

decades. However, digital skills yielded by far the greatest return increase, followed by social skills and far ahead of cognitive skills.

10. Conclusion

In this paper, we develop new measures of worker skills based on skill requirements in apprenticeship plans, which are standardized nationwide across Germany. We identify the complete range of skills acquired during apprenticeship, a total of more than 13,000 narrowly-defined skills, and use information on the duration of learning each skill to construct precise and easily interpretable measures of skill intensity. We group the detailed skills into six broader skill categories: cognitive, social, digital, manual, management, and admin. Merging our skill data with administrative data over almost three decades, we investigate the economic value of workers' early-career skills over the life cycle.

We find that workers who start their labor market career with higher cognitive, social, or digital skills earn significantly higher wages over long-run horizons. Returns to these skills differ, however: For instance, 16-20 years after apprenticeship completion, one additional month of learning cognitive skills during apprenticeship is associated with 1.3% higher wages, while returns to social and digital skills are even larger at 1.5% and 2.1%, respectively. These estimates correspond to 16%-27% of the returns to a full year of schooling, showing the economic value of acquired early-career skills. Results are robust to rigorously controlling for selection into apprenticeships and do not simply reflect returns to occupations.

Investigating drivers of returns to skills, we find evidence for skill complementarities: Workers who simultaneously acquired cognitive and social skills during apprenticeship are particularly valuable on the labor market and are able to sustain this pay advantage throughout their careers. Linking our skill data with job vacancy data, we also provide evidence for skill-technology complementarities. We show that workers with higher cognitive skills earn higher wages in regions in which firms' production technology is more likely to require these skills. When exploring long-run patterns, we observe growth in returns to cognitive, social, and digital skills over the past 30 years. In particular, returns to digital skills have risen substantially, suggesting technology as a major driving force behind the increased economic value of these skills.

More generally, our paper aims to contribute to the understanding of the sources and possible future developments of labor market returns to vocational education. For example, analysis of over-time changes of returns to different types of skills may help to project the impact of technological change on differently-skilled workers and to determine the feasibility of reskilling. Our results also suggest that the German apprenticeship system – which is highly praised internationally (The Economist, 2018) – can indeed serve as a role model. In fact, several countries are currently debating about installing an apprenticeship system.[49] In the U.S., for instance, apprenticeship training has recently been advocated as a means to decrease youth unemployment, increase workforce quality, and provide in-demand skills (Lerman, 2022). By offering insights into the aptness of apprenticeship programs in preparing individuals for the demands of the labor market, our results can provide guidance for the design of vocational training curricula.

[49] See Wolter and Ryan (2011) for an international overview of apprenticeship systems.

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Appendix A. Early-Career Skills

Appendix A.1. Apprenticeship Plans

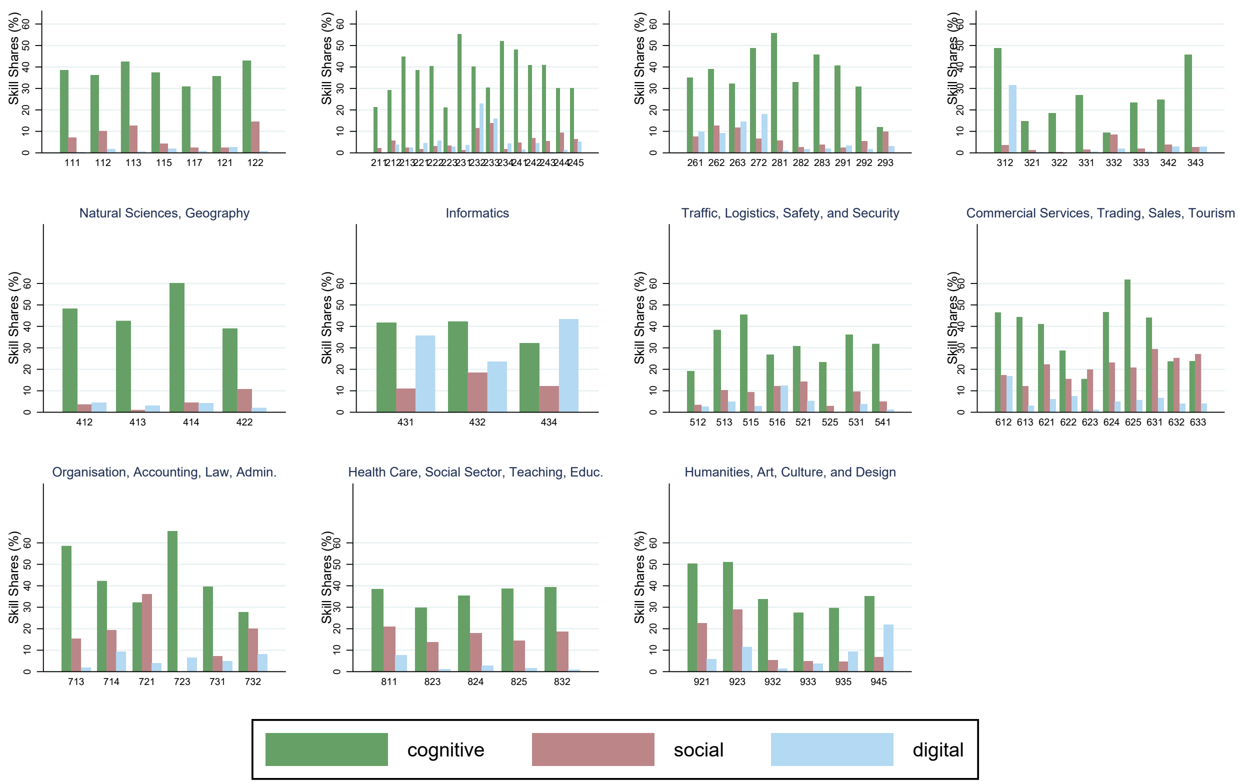
Table A.1: Examples for Skill Labels in Apprenticeship Plans

Occupational Skills	Phrases in Apprenticeship Plans
Cognitive	Assessing and evaluating Examining and certifying Use technical terms in foreign languages Determine and define work steps Implementation of quality assurance measures
Social	Solve conflicts in a team Conduct customer conversations appropriate to the situation Plan and work on tasks in a team Presentation of results Contribute to the prevention of communication difficulties
Digital	Record and evaluate data relevant to the business Integrating IT systems into networks Install and configure operating systems and application programs Distinguish network architectures Use tools and test programs

Appendix A.2. Within-Occupational Variation in Early-Career Skills

Our skill measures line up well with occupational titles and perceived job skills: For instance, Figure A.1 demonstrates that, among the apprenticeships in our sample, IT apprenticeships (KldB 43) have the highest proportion of months dedicated to learning digital skills. Further, there is considerable variation in apprenticeship skill intensities even within 2-digit occupation categories. For instance, in commercial services, trading, sales, and tourism occupations, an e-commerce salesperson (KldB 612) is much more likely to require digital skills than a car salesperson (KldB 622).

Figure A.1: Variation in Early-Career Skills by Occupational Field



Notes: Figure depicts the number of months of learning cognitive, social, and digital skills (as a share of all months of apprenticeship training) for 3-digit apprenticeship occupations, separately by occupational group. Occupations are classified by KldB 2010 ("Klassifikation der Berufe", which translates to Classification of Occupations). Sample includes the 165 largest apprenticeship occupations in Germany.

Appendix A.3. Examples of Occupations with High/Little Intensity of Cognitive, Social, and Digital Skills

Table A.2 lists the top-three and bottom-three apprenticeship occupations in terms of cognitive, social, and digital skills. Panel A shows that physical laboratory technicians, materials testers, and paint lab technicians learn cognitive skills for at least 24 months during their apprenticeship. Computer science experts with a focus on system integration or software development, as well as geomatics engineers, learn more than 14 months of digital skills. Bank clerks learn almost 18 months of social skills, which is far more than in the next-highest occupations (social insurance clerks and fitness clerks, learning social skills for 14 and 11 months, respectively).

Panel B of Table A.2 displays the apprenticeships which provide the least skills in the respective skill domain. Apprenticeships as painters, carpenters, and bakers provide the least cognitive skills. Building construction workers, track layers, and carpenters are among the occupations with the lowest digital skills, and in fact do not provide any digital skills at all. Social skills are lowest in apprenticeships such as interior construction workers, chemistry workers, and civil engineers, which do not provide any digital skills either. Overall, Table A.2 shows that our skill measures line up well with the skill contents one would expect the respective apprenticeship occupations to exhibit.

Table A.2: Top and Bottom Apprenticeships for Cognitive, Social, and Digital Skills

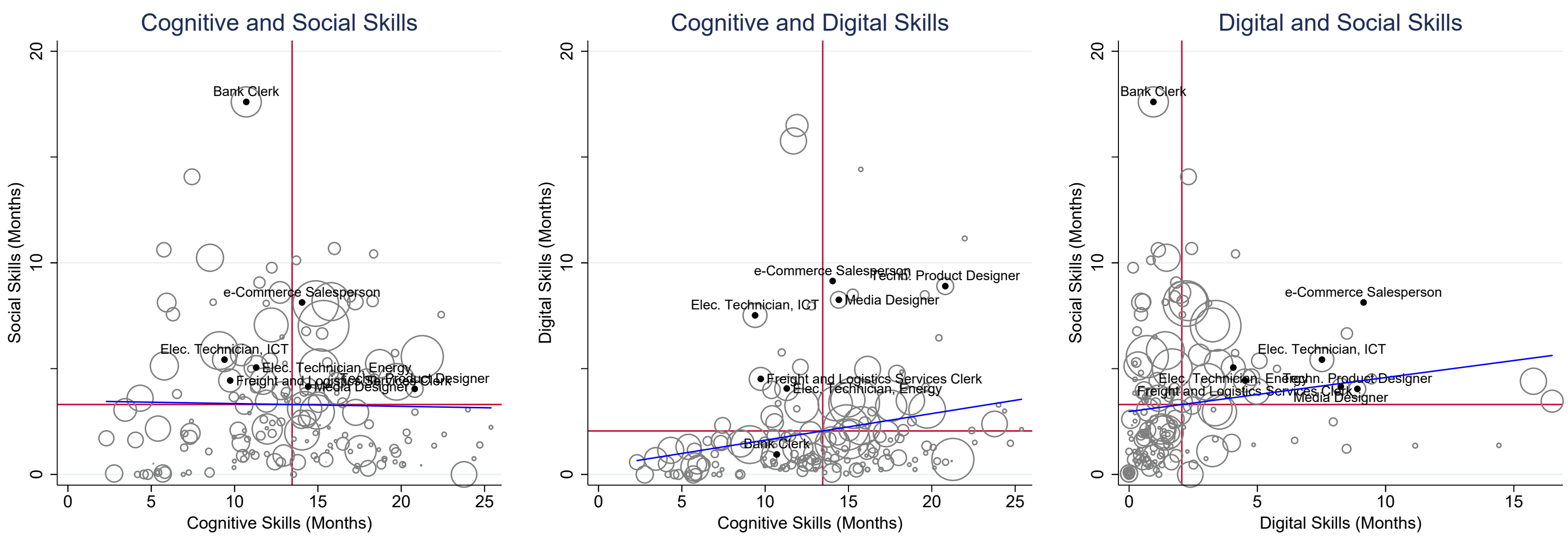
Panel A: Top 3 Apprenticeships											
Cognitive Skills				**Social Skills**				**Digital Skills**			
Occupation	Cog	Dig	Soc	Occupation	Soc	Cog	Dig	Occupation	Dig	Cog	Soc
Phys. Lab. Techn.	25.38	2.13	2.23	Bank Clerk	17.61	10.70	0.95	Comp. Systems	16.49	11.91	3.46
Materials Tester	24.72	1.47	1.40	Soc. Insurance	14.07	7.44	2.32	Comp. Software	15.76	11.70	4.40
Paint Lab Techn.	24.37	3.0	0.75	Fitness Clerk	10.68	15.99	2.44	Geom. Engineer	14.42	15.74	1.38
Panel B: Bottom 3 Apprenticeships											
Cognitive Skills				**Social Skills**				**Digital Skills**			
Occupation	Cog	Dig	Soc	Occupation	Soc	Cog	Dig	Occupation	Dig	Cog	Soc
Painter	3.43	0.74	3.05	Interior Constr.	0.00	4.18	0.00	Build. Constr.	0.00	4.56	0.00
Carpenter	2.78	0.00	0.05	Chem. Worker	0.00	6.92	0.00	Track Layer	0.00	7.25	0.09
Baker	2.31	0.58	1.71	Civil Engineer	0.00	4.80	0.00	Carpenter	0.00	2.78	0.05

Notes: Table shows the ranking of the top and bottom three apprenticeships according to their cognitive, social, and digital skill content (in months) for the 165 largest apprenticeship occupations in Germany. For instance, an apprentice who has completed a Computer Scientist - System Integration (Comp. Systems) apprenticeship has learned digital skills for 16.49 months, cognitive skills for 11.91 months, and social skills for 3.46 months.

Appendix A.4. Apprenticeship Skill Landscape

Figure A.2 plots the cognitive, social, and digital skills in the German apprenticeship system. There is a substantial amount of variation in the skill content of apprenticeship plans, even within occupational fields. For instance, a bank clerk learns substantially more social skills than a freight and logistics services clerk, while both apprenticeships impart about the same amount of cognitive skills (left panel). For digital skills, we observe that electronics technicians for energy learn much fewer digital skills than electronics technicians with a focus on information and communication technologies (ICT), while both learn about the same amount of cognitive skills. Similarly, a media designer and a technical product designer learn about the same amount of digital skills, while an apprenticeship in media design is much less cognitive-skill intense (middle panel). In the right panel, we also see that technical product designers exhibit much fewer social skills than e-commerce salespersons, while both have about the same amount of digital skills.

Figure A.2: Cognitive, Social, and Digital Skills Provided by the German Apprenticeship System



Notes: Figures plot cognitive, social, and digital skills (measured in months of learning a specific skill) in the 165 largest German apprenticeship occupations. The size of the hollow circles around the filled dots is proportional to the number of new apprentices in an occupation in 2017. Regression line shown in blue. Averages of cognitive, social, and digital skills (weighted by the number of new apprentices in 2017) are shown as red lines.

Appendix A.5. Validation

Correlation with Dengler and Matthes (2018) (DM) Measures. To cross-validate our skill measures, we show that the skills we derive from apprenticeship plans correlate strongly with other skill classifications at the occupational or individual level. Table A.3 depicts the correlation between our apprenticeship skill measures and the occupational task content measures by Dengler and Matthes (2018) (DM), based on the German BERUFENET database. BERUFENET is comparable to the U.S. O*NET, providing expert assessments on the tasks carried out within an occupation. Dengler and Matthes (2018) distinguish between five task categories based on Autor et al. (2003) to evaluate how likely occupations are to be substituted by automation technologies: non-routine analytical, non-routine interactive, cognitive routine, manual routine, and manual non-routine. The DM measures are available at the 3-digit occupational level. To compare them to the DM measures, we aggregate our skill measures from the 5-digit level to the 3-digit level.

The key takeaway from Table A.3 is that our measures align well with other established measures derived specifically in the German context and show the correlations we would expect: The DM measure for analytical non-routine task content is positively correlated with cognitive, social, and digital skills. The DM interactive non-routine measure is strongly positively correlated with social skills. The DM measure for cognitive routine tasks is positively correlated with cognitive skills. Furthermore, both manual DM measures (manual routine and manual non-routine) show a positive correlation with manual skills and a negative correlation with social and digital skills. This gives us further confidence in the validity of our measures.

We find a similar correlation pattern when we use measures of abstract, routine, and manual tasks from Goos et al. (2014), which are derived from the U.S. Dictionary of Occupational Titles (DOT), the predecessor of O*NET. Results are available upon request.

Table A.3: Correlation of Early-Career Skills with Measures of Occupational Substitution Potential

Skill Category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Cognitive	1.000								
(2) Social	0.072	1.000							
(3) Digital	0.324	0.186	1.000						
(4) Manual	–0.565	–0.613	–0.535	1.000					
(5) Analyt. Non-Routine	0.263	0.229	0.373	–0.472	1.000				
(6) Interact. Non-Routine	0.107	0.716	0.049	–0.545	0.151	1.000			
(7) Cognitive Routine	0.472	0.290	0.655	–0.522	0.262	0.061	1.000		
(8) Manual Routine	0.125	–0.474	–0.279	0.313	–0.499	–0.437	–0.335	1.000	
(9) Manual Non-Routine	–0.685	–0.230	–0.453	0.633	–0.414	–0.193	–0.575	–0.226	1.000

Notes: Validation exercise with task measures derived by Dengler and Matthes (2018), which approximate the automation probability of occupations based on the BERUFENET data. Correlations are based on individual-level data from our main estimation sample of full-time workers (see Section 4). *Data source:* SIAB.

Appendix B. Further Results

Table B.1: Wage Returns to Early-Career Skills: All Skill Domains

	Log daily wages after			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Cognitive skills (months)	0.008	0.010**	0.011**	0.013***
	(0.0050)	(0.0045)	(0.0044)	(0.0042)
Social skills (months)	0.007	0.013**	0.016***	0.015***
	(0.0055)	(0.0053)	(0.0051)	(0.0049)
Digital skills (months)	–0.004	0.010	0.017**	0.021***
	(0.0056)	(0.0065)	(0.0077)	(0.0080)
Admin skills (months)	0.003	–0.001	–0.001	0.000
	(0.0045)	(0.0049)	(0.0059)	(0.0064)
Management skills (months)	0.030	0.030	0.038	0.032
	(0.0224)	(0.0232)	(0.0238)	(0.0246)
Manual skills (months)	–0.002	–0.002	–0.002	0.000
	(0.0029)	(0.0028)	(0.0032)	(0.0033)
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
F-statistic (all skills)	1.7	4.9	7.0	8.1
N (individuals)	66,432	66,432	66,432	66,432

Notes: Sample consists of male workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. worker characteristics are nationality, age fixed effects, and pre-apprenticeship educational degree. Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Table B.2: Wage Returns to Early-Career Skills: Unrestricted Sample

	Log daily wages after			
	1–5 yrs	6–10 yrs	11–15 yrs	16–20 yrs
	(1)	(2)	(3)	(4)
Cognitive skills (months)	0.016***	0.016***	0.015***	0.015***
	(0.0053)	(0.0049)	(0.0046)	(0.0044)
Social skills (months)	0.014**	0.017***	0.019***	0.017***
	(0.0061)	(0.0054)	(0.0054)	(0.0051)
Digital skills (months)	–0.003	0.007	0.016**	0.024***
	(0.0061)	(0.0071)	(0.0078)	(0.0082)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
F-statistic (all skills)	4.0	6.6	8.5	10.6
N (individuals)	204,007	155,816	111,609	78,898

Notes: Sample consists of workers with a completed apprenticeship training who have at least one full-time employment spell in the period indicated in the column header. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. worker characteristics are nationality, age fixed effects, and pre-apprenticeship educational degree. Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data source:* SIAB.

Table B.3: Wage Returns to Early-Career Skills: Gender Heterogeneity

	Log daily wages after			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Panel A: Males				
Cognitive skills (months)	0.005	0.007	0.009*	0.010**
	(0.0047)	(0.0044)	(0.0043)	(0.0042)
Social skills (months)	0.003	0.009*	0.013**	0.014***
	(0.0051)	(0.0049)	(0.0050)	(0.0048)
Digital skills (months)	–0.004	0.012*	0.019***	0.024***
	(0.0055)	(0.0060)	(0.0070)	(0.0069)
F-statistic (all skills)	0.7	3.6	6.3	7.7
N (individuals)	47,827	47,827	47,827	47,827
Panel B: Females				
Cognitive skills (months)	0.015**	0.014**	0.012*	0.013*
	(0.0060)	(0.0063)	(0.0072)	(0.0067)
Social skills (months)	0.016***	0.018***	0.018**	0.014**
	(0.0058)	(0.0062)	(0.0071)	(0.0067)
Digital skills (months)	0.006	0.007	0.008	0.013
	(0.0107)	(0.0102)	(0.0114)	(0.0113)
F-statistic (all skills)	7.6	9.9	12.6	12.1
N (individuals)	18,605	18,605	18,605	18,605
Further controls	Yes	Yes	Yes	Yes

Notes: Sample consists of male workers (Panel A) and female workers (Panel B) with a completed apprenticeship training. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is mean log daily wages in a 5-year period after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. All models control for the other skill groups (manual, management, admin), worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree), and apprenticeship controls (year of completion, county of training establishment, and occupational field (1-digit)). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Table B.4: Wage Returns to Early-Career Skills: Establishment Size Heterogeneity

	Log daily wages after			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Panel A: Small Apprenticeship Establishments				
Cognitive skills (months)	0.009	0.012**	0.015***	0.016***
	(0.0060)	(0.0054)	(0.0048)	(0.0044)
Social skills (months)	0.003	0.012	0.017*	0.016*
	(0.0103)	(0.0103)	(0.0092)	(0.0081)
Digital skills (months)	–0.005	0.010	0.019**	0.026***
	(0.0065)	(0.0070)	(0.0073)	(0.0074)
F-statistic (all skills)	1.7	6.4	10.0	13.0
N (individuals)	29,374	29,374	29,374	29,374
Panel B: Large Apprenticeship Establishments				
Cognitive skills (months)	0.006	0.006	0.006	0.009**
	(0.0038)	(0.0036)	(0.0038)	(0.0038)
Social skills (months)	0.009**	0.013***	0.015***	0.015***
	(0.0034)	(0.0033)	(0.0036)	(0.0036)
Digital skills (months)	0.002	0.015**	0.022***	0.025***
	(0.0048)	(0.0058)	(0.0074)	(0.0080)
F-statistic (all skills)	1.6	4.9	6.2	6.1
N (individuals)	37,058	37,058	37,058	37,058
Further controls	Yes	Yes	Yes	Yes

Notes: Regression results are shown separately for workers who finished their apprenticeship in a "small" establishment (1-37 employees) in Panel A vs. a "large" establishment (38-16,870 employees) in Panel B. Size categories are based on a median split in the number of full-time employees at apprenticeship completion. Sample consists of full-time workers with a completed apprenticeship training. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is log daily wages by years after apprenticeship completion (e.g., Column 1 corresponds to the mean log daily wages in years 1 to 5 after apprenticeship completion). Early-career skills are measured in months of learning the respective skill during the apprenticeship. All models control for the other skill groups (manual, management, admin), worker characteristics (nationality, age fixed effects, and pre-apprenticeship educational degree), and apprenticeship controls (year of completion, county of training establishment, and occupational field (1-digit)). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Appendix C. Mechanisms

In this appendix, we investigate channels for the estimated wage returns to skills. We consider investment in human capital after apprenticeship completion, occupational switching, firm-specific rents, and employer learning as potential mechanisms.

Appendix C.1. Human Capital Investments

We start by analyzing whether certain early-career skills are more strongly related to further educational attainment after apprenticeship completion. Table C.1 provides results analogous to those in Table 5 using an indicator of having obtained a university degree as dependent variable. The results show that higher cognitive skills are not significantly related to further investment in formal education after labor market entry. Workers with higher social skills are significantly more likely to obtain further education. 16-20 years after apprenticeship completion, we observe an increase in the probability to obtain university education by 0.34 percentage points for an additional month of social skills, which translates to an increase by 4% relative to mean university completion in the sample. However, the likelihood of individuals who acquired more digital skills during apprenticeship to obtain a university degree is by an order of magnitude higher. Already in the first five years after apprenticeship completion, a one-month increase in learning digital skills is associated with a 0.31 percentage-point increase in university completion, which translates to an effect size of 14%. After 16-20 years, we even observe an increase by 1.3 percentage points (15.5%) for an additional month of learning digital skills during vocational education. These results suggest that further investing in formal education is one explanation for the returns to social skills and particularly for the returns to digital skills over the career.

Our administrative worker data does not contain information on learning on the job. To see how early-career skills are related to non-formal adult education, we resort to survey data from PIAAC. Respondents in PIAAC are asked whether they have participated in training on-the-job in the 12 months prior to the survey. Table C.2 shows that particularly higher digital skills are associated with a higher engagement of workers in non-formal adult learning activities, while cognitive and social skills are not robustly related to training. Panel A reports results for full-time workers aged 35-65, i.e., the same age restriction as in the PIAAC wage analysis. In Panel B, we focus on full-time workers below age 40, i.e., roughly the same age range as for the labor market entrants whom we follow over their careers in our administrative worker data. While significant in both worker samples, the positive association of digital skills with training participation is substantially larger for younger workers: With all controls, a one-month increase in digital skills is associated with an increase in the probability to participate in training of 4.8 percentage points (10.5%) in the sample of younger workers and with an increase of 1.8 percentage points (4%) in the sample of older workers.

One interpretation of these results is that training activities – especially at younger ages – secure employability of digital-intense workers in light of accelerating technological change. This is consistent with the evidence from Deming and Noray (2020), who show that skills depreciate faster in digital-intense occupations. They further show that high-wage digital workers frequently change occupations to avoid decreasing returns to their skills due to skill obsolescence as they gain experience.

Appendix C.2. Occupational Change, Firm-Specific Rents, and Employer Learning

In Table C.3, we investigate occupational mobility as anther potential channel for returns to skills over the career. Intriguingly, neither cognitive nor digital skills are systematically related to occupational switching. Together with the evidence on educational upgrading from the previous section, this suggests that workers with higher digital skills rather invest in their human capital to keep their knowledge up-to-date than switch occupations. Intriguingly, higher social skills decrease the likelihood to change occupations. For instance, a one-month increase in social skills is related to a decrease by 2.3 percentage points (2.9% relative to the average switching probability) in the probability to be observed in an occupation other than the apprenticeship occupation 16-20 years after apprenticeship completion. Thus, higher social skills allow workers to stay in their apprenticeship occupation.

Next, we analyze whether returns to skills can be explained by firm-specific rents. It may be that certain early-career skills increase the likelihood that an apprentice is hired by the training firm after the apprenticeship is completed, potentially benefiting from firm-specific rents. However, over three-quarters (76%) of apprentices in our data start their labor market career with the training firm. Still, we find that apprentices with higher cognitive or social skills are significantly more likely to be hired by the training firm, while digital skills are not significantly related to the probability to start the career with the training firm. However, the economic magnitude of these associations is small: A one-month increase in cognitive skills increases the probability to remain at the training firm by 0.09 percentage points, a one-month increase in social skills is associated with an increase by 0.06 percentage points. This suggests that firm-specific rents are unlikely to be a major driver of the observed pattern of skill returns.

Relatedly, a potential reason for the increasing earnings gradient for skills over the career would be employer learning. Because skills are difficult to observe, it may take time for firms to learn about relevant differences among workers (e.g., Altonji and Pierret, 2001). However, the fact that more than three-quarters of workers stay with their training firm when entering the labor market suggests that employer learning is unlikely to drive the observed increase in returns over the life cycle, as workers have already spent several years with the training when we start to track their wages. The German setting where trained workers' skills are codified in apprenticeship plans also suggests a minor role for employer learning even for workers who switch firms, because the new firm should have a good command of the skills a worker possesses.

Table C.1: Mechanisms: Educational Upgrading

	University education (× 100)			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Cognitive skills (months)	–0.030	0.001	0.004	0.013
	(0.0380)	(0.0629)	(0.0821)	(0.0936)
Social skills (months)	–0.038	0.151**	0.282***	0.336***
	(0.0486)	(0.0708)	(0.0823)	(0.1080)
Digital skills (months)	0.312***	0.901***	1.150***	1.310***
	(0.1110)	(0.2170)	(0.2860)	(0.3040)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
Outcome mean (in percent)	2.24	5.07	6.90	8.46
F-statistic (all skills)	5.4	6.1	6.3	6.3
N (individuals)	66,432	66,432	66,432	66,432

Notes: Sample consists of full-time workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is a binary indicator of university education, taking a value of 1 if the worker obtains a university degree in the period indicated in the column header, and 0 otherwise. Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (gender, nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Table C.2: Early-Career Skills and Job Training (PIAAC)

	On-the-Job Training			
	(1)	(2)	(3)	(4)
Panel A: Age 35–65				
Cognitive skills (months)	0.005	0.005	0.001	0.003
	(0.006)	(0.006)	(0.007)	(0.007)
Social skills (months)	0.009	0.006	0.004	0.005
	(0.006)	(0.006)	(0.007)	(0.007)
Digital skills (months)	0.022**	0.018**	0.020**	0.018*
	(0.009)	(0.008)	(0.010)	(0.010)
Outcome mean	0.44			
F-statistic (all skills)	2.4	2.6	1.4	1.5
N (individuals)	739	739	739	739
Panel B: Below Age 40				
Cognitive skills (months)	0.017*	0.017*	0.014	0.016*
	(0.010)	(0.009)	(0.008)	(0.009)
Social skills (months)	0.014	0.015	0.007	0.009
	(0.017)	(0.016)	(0.019)	(0.019)
Digital skills (months)	0.047***	0.047***	0.045***	0.048***
	(0.013)	(0.013)	(0.012)	(0.012)
Outcome mean	0.46			
F-statistic (all skills)	2.9	2.9	3.0	3.3
N (individuals)	418	418	418	418
Baseline controls	Yes	Yes	Yes	Yes
High-school grades	No	Yes	Yes	Yes
Family background	No	No	Yes	Yes
Non-cognitive skills	No	No	No	Yes

Notes: Sample consists of full-time workers aged 35-65 years (Panel A) or aged 16-39 years (Panel B) with a completed apprenticeship training. Dependent variable is an indicator of training on-the-job, which takes a value of 1 if the person has participated in an on-the-job training during the 12 months prior to the survey, and 0 otherwise. Early-career skills are measured in months of learning the respective skill during the apprenticeship. Baseline controls include the other skill domains (manual, management, admin), worker characteristics (gender, migrant status, quadratic polynomial in age, and highest educational degree (8 categories)), and 1-digit apprenticeship occupation fixed effects. High-school grades are final grades in math, German, and foreign language upon completing secondary education. Family background comprises the highest level of education obtained by the respondent's mother/father in three categories (no vocational or university education, vocational, university) and the occupation of the mother/father when the respondent was 15 years old (2-digit level). Non-cognitive skills include the Big 5 personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) and grit. Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* PIAAC.

Table C.3: Mechanisms: Occupational Switching

	Occupational switching after			
	1–5 yrs (1)	6–10 yrs (2)	11–15 yrs (3)	16–20 yrs (4)
Cognitive skills (months)	–0.004	–0.001	0.000	0.002
	(0.0035)	(0.0033)	(0.0036)	(0.0038)
Social skills (months)	–0.018***	–0.014***	–0.018***	–0.023***
	(0.0047)	(0.0041)	(0.0046)	(0.0050)
Digital skills (months)	–0.011	–0.001	0.000	0.005
	(0.0080)	(0.0081)	(0.0071)	(0.0055)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship controls				
Completion year FE	Yes	Yes	Yes	Yes
County of establishment FE	Yes	Yes	Yes	Yes
Occupation FE (1-digit)	Yes	Yes	Yes	Yes
Outcome mean	0.52	0.60	0.68	0.79
F-statistic (all skills)	2.9	2.9	3.4	6.0
N (individuals)	66,432	66,432	66,432	66,432

Notes: Sample consists of full-time workers with a completed apprenticeship training whom we can follow in the first four consecutive 5-year periods after labor market entry. To be included in the sample, a worker needs to be observed at least once in full-time employment in each of the four consecutive 5-year periods. If a worker has completed more than one apprenticeship, we consider only the first apprenticeship to measure early-career skills. Dependent variable is a binary indicator of occupational switching, taking a value of 1 if a worker is observed at least once in an occupation different from the apprenticeship occupation (4-digit level) in the period indicated in the column header, and 0 otherwise. Early-career skills are measured in months of learning the respective skill during the apprenticeship. We control for the other skill groups (manual, management, admin) and worker characteristics (gender, nationality, age fixed effects, and pre-apprenticeship educational degree). Apprenticeship controls contain year of completion, county of training establishment, and occupational field (1-digit). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* SIAB.

Appendix D. PIAAC Results

Table D.1: Early-Career Skills and Test Scores (PIAAC)

	PIAAC Test Scores		
	Numeracy (1)	Literacy (2)	ICT (3)
Cognitive skills (months)	0.018***	0.014*	0.008
	(0.007)	(0.008)	(0.008)
Social skills (months)	0.021***	0.015*	0.001
	(0.007)	(0.008)	(0.009)
Digital skills (months)	0.032***	0.030**	0.031***
	(0.009)	(0.012)	(0.012)
All skills	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes
F-statistic (all skills)	17.1	10.6	12.3
N (individuals)	1,612	1,612	1,365

Notes: Sample consists of PIAAC respondents with a completed apprenticeship training. Dependent variables are test scores in numeracy (Column 1), literacy (Column 2), problem-solving in technology-rich environments, which we refer to as ICT skills (Column 3). The smaller number of observations in Column 3 is due to the fact that ICT skills could not be tested for respondents who did not participate in PIAAC in a computer-based mode. There are three reasons for why respondents did not participate in a a computer-based mode (see Falck et al., 2021): (i) individuals had no prior computer experience; (ii) individuals failed a computer core test, which assessed basic digital competencies such as using a keyboard/mouse or scrolling through a web page; (iii) individuals refused to take part in the computer-based assessment. All test scores are standardized with standard deviation 1 in the entire PIAAC sample. Early-career skills are measured in months of learning the respective skill during the apprenticeship. All specifications control for the other skill domains (manual, management, admin) and worker characteristics (gender, migrant status, quadratic polynomial in age, and highest pre-apprenticeship educational degree (8 categories)). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* PIAAC.

Table D.2: Early-Career Skills and Job Tasks (PIAAC)

	Task Content					
	Numeracy (Simple) (1)	Numeracy (Advanced) (2)	Social (3)	Experience w/ Computer (4)	Computer Use (5)	Internet Use (6)
Cognitive skills (months)	0.014	0.005	–0.001	0.008	0.001	–0.006
	(0.011)	(0.009)	(0.013)	(0.006)	(0.019)	(0.017)
Social skills (months)	0.006	0.002	0.026*	0.009	–0.000	–0.012
	(0.015)	(0.014)	(0.014)	(0.007)	(0.019)	(0.023)
Digital skills (months)	–0.005	0.023*	–0.009	0.023***	0.061***	–0.003
	(0.013)	(0.012)	(0.014)	(0.007)	(0.020)	(0.013)
All skills	Yes	Yes	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic (all skills)	4.3	3.4	8.2	10.6	4.6	4.9
N (individuals)	1,414	1,413	1,411	1,414	1,025	1,026

Notes: Sample consists of PIAAC respondents with a completed apprenticeship training. Dependent variables measure the task content of a worker's current job in several dimensions: Simple numeracy tasks (Column 1), advanced numeracy tasks (Column 2), social tasks (Column 3), experience with computers (Column 4), computer use (Column 5), and internet use (Column 6). The smaller number of observations in Columns 5 and 6 are due to the fact that ICT task use at work questions were not asked to respondents who do not use a computer at work. The simple numeracy tasks index is based on questions examining how often a respondent performs the following activities at work: calculating costs or budgets, use or calculate fractions or percentages, use a calculator, and prepare charts, graphs, or tables. The advanced numeracy tasks index is based on questions asking how often respondents use algebra or formulas and advanced math or statistics at the job. To construct the social tasks index, we use questions asking how often respondents perform the following activities at the job: advising people, influencing people, negotiating with people, selling. The experience with computer indicator is based on a question asking whether respondents have experience with computers in their job. The computer use index is based on questions asking respondents how often they perform the following activities at work: use spreadsheets, word, programming language, and real-time discussions. The internet use index is based on questions on how often a respondent uses the internet for the following purposes: mail, acquiring work-related information, and conducting transactions. Answer categories (with the exception of the computer experience indicator) are on a 5-point scale that ranges from never to every day. Following the procedure by Kling et al. (2007), we construct the task indices as an equally weighted average of the z-scores of the included items. The resulting index is again standardized with standard deviation 1 in the entire PIAAC sample. Early-career skills are measured in months of learning the respective skill during the apprenticeship. All specifications control for the other skill domains (manual, management, admin) and worker characteristics (gender, migrant status, quadratic polynomial in age, and highest pre-apprenticeship educational degree (8 categories)). Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data source:* PIAAC.

Table D.3: Wage Returns to Early-Career Skills (PIAAC)

	Log hourly wages			
	(1)	(2)	(3)	(4)
Cognitive skills (months)	0.021***	0.019***	0.020***	0.020***
	(0.006)	(0.006)	(0.007)	(0.007)
Social skills (months)	0.029***	0.028***	0.027***	0.026***
	(0.007)	(0.007)	(0.008)	(0.008)
Digital skills (months)	0.014	0.013	0.018*	0.017*
	(0.009)	(0.009)	(0.010)	(0.010)
All skills	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Apprenticeship occupation FE (1-digit)	Yes	Yes	Yes	Yes
High-school grades	No	Yes	Yes	Yes
Family background	No	No	Yes	Yes
Non-cognitive skills	No	No	No	Yes
F-statistic (all skills)	7.2	6.5	6.6	7.0
N (individuals)	613	613	613	613

Notes: Sample consists of full-time workers aged 35-65 years with a completed apprenticeship training. Dependent variable is log hourly wages. Early-career skills are measured in months of learning the respective skill during the apprenticeship. All specifications control for the other skill domains (manual, management, admin), worker characteristics (gender, migrant status, quadratic polynomial in age, and highest pre-apprenticeship educational degree (8 categories)), and 1-digit apprenticeship occupation fixed effects. High-school grades are final grades in math, German, and foreign language upon completing secondary education. Family background comprises the highest level of education obtained by the respondent's mother/father in three categories (no vocational or university education, vocational, university) and the occupation of the mother/father when the respondent was 15 years old (2-digit level). Non-cognitive skills include the Big 5 personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) and grit. Robust standard errors, shown in parentheses, are clustered at the level of the apprenticeship occupation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* PIAAC.