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The Value of Practical Skills

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Abstract

Practical skills are widely believed to be a key determinant of labor market success, yet credible empirical evidence remains scarce, because these skills are occupation-specific, acquired primarily through workplace experience, and notoriously difficult to measure. We address these challenges using an exceptional dataset covering over 170 occupations. Our measure of practical skills is based on high-stakes expert evaluations of apprentices' performance in occupation-specific standardized practical examinations, conducted under authentic workplace conditions and lasting from several hours to several weeks. Combined with rich administrative data, this allows us to separate practical skills from general and vocational knowledge. We show that practical skills form a distinct dimension of human capital, only weakly correlated with traditional achievement measures. Practical skills are the strongest predictor of early labor market success, consistently associated with higher first-year earnings, lower NEET risk, greater retention by the training firm, and a higher likelihood of entering tertiary education. These relationships are robust across occupational task groups and by gender. Out-of-sample analyses show that practical skills substantially improve predictions beyond conventional educational achievement and background characteristics.

JEL classification

J24, I26, J31

Keywords

return to skills, practical skills, school-to-work transition, human capital

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"Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity."

— *Kenneth J. Arrow (1962)*

1 Introduction

Economists have long emphasized the importance of practical skills for economic success. Individual productivity, innovation, and economic growth have repeatedly been linked to practical skills rather than to general knowledge or school-based competencies such as literacy and numeracy (De La Croix et al., 2018; Kelly et al., 2014, 2023). Yet for decades empirical research proxied human capital almost exclusively by years of schooling, a measure that distinguishes neither dimensions nor levels of skill (Card, 2001; Mincer, 1974). Only more recently have economists shifted attention from schooling to skills, showing that measured competencies predict earnings above and beyond formal educational attainment (Deming, 2017; Hanushek et al., 2015; Heckman et al., 2006). Building on the notion that productivity reflects a portfolio of skills weighted by occupational requirements (Lazear, 2009), a growing literature infers multidimensional skill requirements and worker endowments from job postings, training curricula, and online worker profiles (Cnossen et al., 2025; Deming & Kahn, 2018; Dorn et al., 2025; Eggenberger et al., 2018; Kiener et al., 2022; Langer & Wiederhold, 2023; Lise & Postel-Vinay, 2020).

While there is broad agreement that years of schooling, standardized test scores, and similar one-dimensional measures fail to capture the skill variation relevant for productivity (Deming & Silliman, 2025), there has been remarkably little direct evidence on the economic importance of practical or tacit skills. This gap reflects several measurement challenges. First, practical or tacit skills cannot be acquired through formal education alone; they develop through experience, observation, imitation, feedback, and repeated practice (Arrow, 1962; Foray, 2004; Gertler, 2003). Assessing them therefore requires observing individuals who have already spent years acquiring and refining them in occupational practice. Second, practical skills are difficult to codify and operationalize, and therefore to measure. Third, the relevant practical skills differ across occupations, so any assessment must be defined on an occupation-specific basis. Finally, practical skills reveal themselves only when individuals solve authentic problems, which requires assessment settings well beyond conventional school examinations, theoretical competency tests, or simulated problem solving. The scarcity of direct evidence thus reflects not doubts about the importance of practical skills, but the inherent difficulty of defining and measuring them.

In this paper, we examine how revealed practical skills relate to short-term labor market outcomes using a novel individual-level measure of demonstrated practical performance. Our measure exploits a distinctive feature of the Swiss apprenticeship system. After three or four years of combined school- and firm-based training, apprentices must pass a final examination whose components we observe separately. General knowledge and vocational knowledge are assessed through standardized written or oral examinations. Demonstrated practical performance, by contrast, is evaluated through an individual or predefined occupation-specific project explicitly designed to assess "practical skills in a real-world work setting" (SERI, 2019). These projects are completed in the training firm or a training center, last from several hours to several weeks, and are graded independently by two trained experts recruited from among industry professionals. The resulting grade provides a standardized measure of demonstrated occupation-specific competence that is directly comparable across individuals within the same occupation. Throughout the paper, we therefore refer to this measure as revealed practical skills in the tasks that characterize their occupation.

We leverage a novel administrative dataset covering six complete cohorts of apprentices in a Swiss canton between 2018 and 2023. These records are linked to rich administrative information on individuals' prior educational histories and their subsequent educational and labor market trajectories through 2024. Because we observe separate grades for general knowledge, vocational knowledge, and practical skills, the data provide a rare individual-level measure of occupation-specific practical skills conditional on other skills at the point of labor market entry. Unlike recent studies that infer workers' skills from job postings, training curricula, or occupational characteristics, our measure captures how individuals actually perform in authentic occupation-specific tasks under standardized assessment conditions.

This setting offers two additional advantages. First, because all three skill dimensions are observed for the same individuals, we can move beyond a one-dimensional notion of ability, identify whether workers possess a comparative advantage in the practical, vocational-theoretical, or general domain, and examine whether demonstrated practical skills contain information beyond the other two dimensions. Second, the linkage to administrative follow-up data allows us to study a broad set of widely used outcomes, including earnings, NEET status, retention by the training firm, and transitions into tertiary education. Together, these features provide an unusually well-suited setting for examining which dimensions of human capital matter most at the beginning of workers' careers.

We find that practical skills constitute a distinct and economically important dimension of human capital. Although the three examination components are positively correlated, they are far from redundant: practical skills are only weakly correlated with both general knowledge and vocational knowledge. When all three dimensions are included simultaneously, practical skills emerge as the strongest and most consistent predictor of early labor market outcomes. A one standard deviation higher practical grade (0.44 grade points) is associated with 1.7 percent higher first-year monthly earnings and a 5.1 percentage point higher probability of remaining with the training firm — in both cases at least twice the association of vocational knowledge and at least three times that of general knowledge — as well as a lower probability of being NEET and a higher likelihood of entering tertiary education. General knowledge is independently associated with several outcomes, particularly transitions into tertiary education, whereas vocational knowledge contributes little additional explanatory power once the other two dimensions are taken into account.

The results are remarkably stable across occupational task groups and gender. Moreover, out-of-sample prediction exercises show that demonstrated practical performance improves predictive accuracy for all major outcomes and matches or outperforms GPA and the other examination components in predicting earnings and retention by the training firm. Finally, a data-driven cluster analysis reveals that individuals with a practice-oriented skill profile perform comparatively well in the labor market even when their overall GPA is unremarkable. Our findings establish practical skills as a distinct dimension of human capital that complements traditional measures of cognitive achievement and helps explain early labor market success.

1.1 Literature

While practical and tacit skills are rarely measured directly in empirical economics, related concepts have been studied extensively in other disciplines, particularly psychology, which established practical skills as a separate intelligence dimension (see Cianciolo et al., 2006, for instance). Notably, Sternberg (1985) distinguished between analytical intelligence (problem-solving and academic reasoning), creative intelligence (generating novel and useful ideas), and practical intelligence (applying knowledge effectively in real-world contexts). Several studies report correlations between tacit knowledge and outcomes such as wages, job performance, and teaching effectiveness (for an overview, see Wagner, 2011). Tacit knowledge — often recurring examples are riding a bicycle, swimming, or the "feel" of a process — has also featured prominently in management research, economic geography, economic history, and the literature on work-based learning (e.g. Cowan et al., 2000; Howells, 2002; Perraton & Tarrant, 2007; Streeck, 2011). Bartelsman et al. (2024) show that a reform removing non-compete agreements in the Netherlands led to higher earnings and argue that it reduced the costs of worker mobility, thereby increasing workers' bargaining power and the returns to tacit knowledge.

Our study makes several contributions to the literature. First, we contribute to our understanding of the labor market value of human capital. The classic returns-to-education literature established that schooling is strongly related to earnings, but it necessarily treats education as a broad proxy for productive attributes (Card, 2001; Mincer, 1974). Later literature opened this black box by showing that measured cognitive, non-cognitive, and social skills explain labor market outcomes beyond formal educational attainment (Deming, 2017; Hanushek et al., 2015; Heckman et al., 2006). The practical dimension of skill, however, was rarely analyzed explicitly, even though it may implicitly drive some of the findings. Our contribution is to show that an important part of this worker heterogeneity is practical and occupation-specific, a dimension central to production in many occupations but rarely observed at the individual level. This matters because practical performance is not simply another measure of general ability: it is only moderately related to general and theoretical grades and predicts early labor market outcomes even when these other dimensions are held constant.

Second, we contribute to the literature on grades and skill signals at labor market entry. Recent evidence shows that employers use grades and other skill signals when young workers enter the labor market, and that such signals affect hiring and earnings when employers have limited information (Hansen et al., 2024; Piopiunik et al., 2020). Existing studies typically focus on aggregate GPA, resume signals, or broad skill domains. We show, first, that the *content* of the grade signal matters: the aggregate GPA gradient masks substantial differences across assessment domains, with vocational practice grades accounting for the most robust part of the association with early labor market success, while general knowledge is more closely related to transitions into higher education. Grades thus do not merely rank students by overall performance; they reveal whether achievement is primarily practical, theoretical, or general, and these distinctions map differently onto early career trajectories. We find, second, suggestive evidence that the *weight* of the signal depends on employer information. The practical-grade premium is larger for graduates who move to a new employer than for those retained by their training firm. This heterogeneity is consistent with employer learning, in which a certified signal matters more for employers who have not directly observed the worker's productivity (Altonji & Pierret, 2001; Farber & Gibbons, 1996), and with the superior information training firms hold about their own apprentices (Mohrenweiser et al., 2020). Notably, this asymmetry is concentrated in vocational practice, the skill domain that is the hardest to observe and codify.

Third, the paper relates to the literature on task-specific human capital. The task-based literature shows that the task content of jobs is central for understanding earnings, mobility, and the transferability of human capital (Autor & Handel, 2013; Autor et al., 2003; Gathmann & Schönberg, 2010). Existing work typically infers skill content from occupations, task classifications, or job postings. We instead observe how well individuals perform the practical component of their own occupation, connecting these perspectives from the worker side. This shifts the focus from the skill requirements of jobs to the realized practical skills of workers. The results show the distinction matters: practical performance is not only descriptively different from general and theoretical achievement but also predicts early labor market outcomes in ways that broad measures of ability do not fully capture.

Finally, practical skills provide a potential mechanism underlying the well-established returns to labor market experience or tenure. The idea that productivity rises with practice rather than instruction goes back to Arrow (1962), and the empirical literature documents that earnings growth over the life cycle is driven more by accumulated experience than by formal education, with earnings increasing most rapidly early in workers' careers (Cingano, 2003; Deming, 2025; Dorn et al., 2025; Dustmann & Meghir, 2005; Rubinstein & Weiss, 2006). If workers acquire practical, often occupation-specific skills through on-the-job learning, the resulting productivity gains and earnings growth should be largest early in the career and in more complex occupations, consistent with the observed shape of earning-experience profiles. Measuring practical skills at labor market entry rather than their accumulation over time, we cannot provide direct evidence on this dynamic, but our cross-sectional results are consistent with practical performance being the kind of human capital this mechanism would predict.

2 Empirical setting

2.1 Institutional background

Switzerland's education system comprises 11 years of compulsory schooling, followed by either an academic or a vocational track at the upper-secondary level. Approximately two-thirds of each cohort choose vocational education and training (VET), making it the dominant upper-secondary pathway. Nearly 90 percent of VET students enroll in the dual apprenticeship system, which combines firm-based training with vocational schooling. Apprentices choose from more than 200 nationally regulated occupations and may complement their training with a professional baccalaureate that provides direct access to universities of applied sciences.

The institutional feature central to our analysis is the nationally standardized final qualification procedure completed by every apprentice. Unlike most educational systems, the Swiss VET examination separately assesses three distinct dimensions of achievement: general knowledge, vocational knowledge, and demonstrated practical performance, which we will label vocational practice in our empirical analyses. The latter is explicitly designed to evaluate apprentices' practical skills through the execution of authentic occupation-specific work tasks under standardized assessment conditions (SERI, 2019). Because these assessments take place immediately before labor market entry and are available for every apprentice, they provide a unique measure of revealed practical skills across a broad range of occupations.

The Swiss VET system is jointly governed by the federal government, the cantons, and occupation-specific professional associations. While the federal government establishes the legal framework and the cantons oversee implementation, professional associations develop the occupational curricula and specify the practical examination for each occupation. Despite this decentralized governance structure, training and assessment are nationally standardized. Apprenticeships typically last three or four years, during which apprentices spend three to four days per week in the training firm and one to two days in vocational school.

The final qualification procedure consists of up to four graded components: general knowledge, vocational knowledge, practical performance (skills), and experience grades based on previous vocational-school achievement. All components are graded on a scale from one (very bad) to six (excellent), with four representing the passing threshold. The overall qualification grade (GPA) is a weighted average of these components, although the weights vary across occupations and are determined by the respective professional associations. In many occupations, passing the practical examination is mandatory and cannot be compensated by stronger performance in other examination components.

General knowledge and vocational knowledge are assessed through standardized written or oral examinations. Demonstrated practical performance, by contrast, is evaluated through authentic occupational tasks that typically require several hours to several weeks to complete, depending on the occupation. Rather than measuring knowledge about occupational tasks, these assessments require apprentices to perform those tasks under realistic working conditions. Consequently, the practical examination captures an aspect of human capital that is difficult to measure through conventional written examinations or questionnaires.

The practical examination takes one of two forms. In the predefined practical examination, all apprentices complete the same standardized tasks specified by the national professional association. In the individual practical examination, apprentices complete a project within their training firm. The project is proposed jointly by the apprentice and the firm's trainer and subsequently approved by the examination committee. Regardless of the examination format, all practical work is evaluated independently by two external experts, who assess both the work process and its outcome, as well as the accompanying documentation, presentation, and technical discussion. Appendix A presents examples of practical examinations across occupations.

The external experts are typically experienced practitioners employed in the occupation they assess. Before serving as examiners, they receive standardized training in the national assessment procedures while continuing their regular professional activities. Their work is coordinated by a chief examiner responsible for ensuring consistent application of the national grading standards. Finally, the national examination commission reviews the results and screens for potential irregularities, further strengthening the comparability of assessment across firms and exam sites.

2.2 Data

We combine several administrative data sources. First, we draw on examination records for all VET students who sat the final qualification examination in the Canton of Aargau between 2018 and 2023. These contain a unique individual identifier, the training occupation, the examination outcome (pass/fail), the overall grade point average (GPA) and its main components (vocational knowledge, vocational practice, general knowledge, and the experience grade), as well as grades for the individual subjects. Using the individual identifier, we link these records to the Swiss educational register, the Longitudinal Analyses in Education (LABB), which tracks educational trajectories and transitions across levels of education and into the labor market, and, as described below, to social-security spell data on employment and earnings.

Our sample consists of 24,452 individuals. However, we face two sources of missing grade information. First, not all examination components exist in every occupation: the training regulations governing each occupation specify the structure and weighting of the assessment components, so component grades are unavailable for some individuals, including those in the single most common occupation, Commercial Employee (*Kaufmann/-frau*). Overall, 5,551 individuals train in an occupation with missing grade elements.

Second, 2,414 individuals are exempt from particular components, especially general knowledge. Exemptions apply, for example, to apprentices who complete a Federal Vocational Baccalaureate alongside their training or who hold an equivalent prior qualification such as an earlier apprenticeship diploma or an academic baccalaureate.[1] After excluding observations

[1]For 294 individuals exempt from general knowledge, we use the general knowledge grade from their previous apprenticeship and include a dummy for these cases in all regressions.

with missing grade components, our analytical sample consists of 16,487 individuals. Although these exclusions are not random, we have no particular reason to expect the relationship between practical performance and labor market outcomes to differ for the under-represented groups, especially given that the estimates are robust across the occupational type and gender subsamples (Section 3.3).

Moreover, the sample covers 173 of roughly 230 occupations. Table 1 reports occupation-level requirement scores, based on expert evaluations of the academic requirements of each occupation. These scores range in principle from 0 (very low requirements) to 100 (very high), although the highest allocated value is 83. In our sample mathematics and language requirements span 4 to 83, indicating that we cover essentially the entire requirement distribution. Scores between 60 and 80 are typical of occupations chosen by individuals whose cognitive skills are comparable to those entering the academic baccalaureate track. The sample is therefore not confined to a narrow set of predominantly manual occupations: only about half of our observations are in occupations classified as manual (Table 1), and the range of requirement scores extends well into the band typical of academically demanding training programs.

For most outcome variables, we use spell data from the Swiss social security system. These records track individuals' labor market status over time: employed, in education, in military service, receiving disability benefits, registered unemployed, or NEET (not in employment, education, or training). Each spell also carries a firm identifier, which we use to determine whether a graduate stays with the training firm or moves to a different employer. We define an individual as a *stayer* if they are employed at their training firm on 31 December of the graduation year (Year 0), and as a *leaver* otherwise. Retention is thus measured as a point-in-time snapshot at the end of the graduation year, whereas the other outcomes (earnings, NEET status, and tertiary entry) are measured over the subsequent year (Year 1).

The spell data additionally contain earnings reported to the tax authorities. Being administrative rather than self-reported, these earnings avoid the recall and measurement error common in survey data. They come with two limitations. First, working hours are not observed, so earnings reflect actual rather than full-time-equivalent pay, and differences in earnings may therefore reflect both earnings rates and hours worked. Second, the Federal Statistical Office records only annual earnings and allocates them to months according to labor market status, which can distort earnings in periods that combine employment and education. To mitigate this, we restrict the earnings analysis to person-years in which the individual was employed throughout the entire calendar year, so that annual earnings are not distorted by spells of education. This also excludes years in which an individual begins tertiary education, as they may then work reduced hours.

2.3 Descriptive statistics

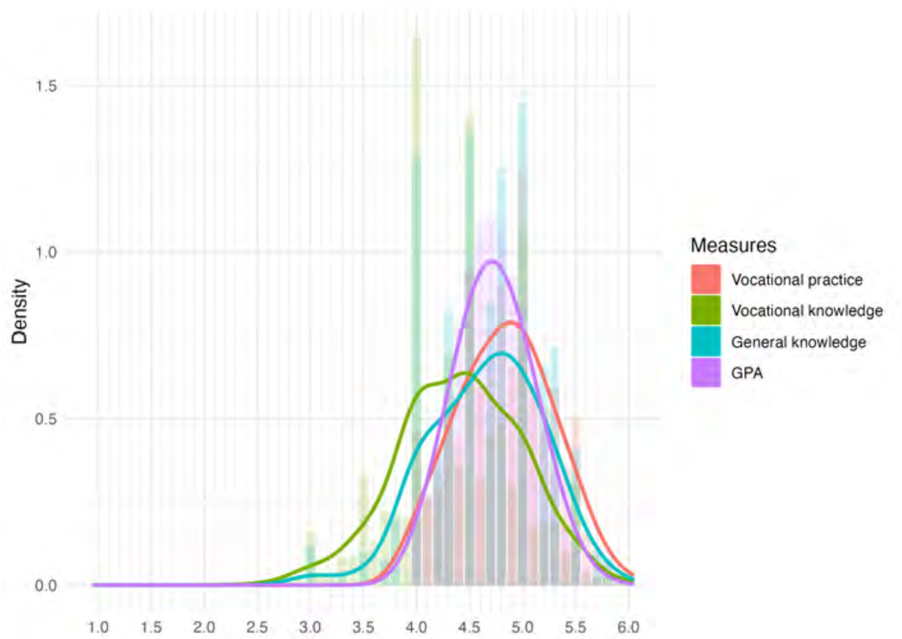
Table 1 reports descriptive statistics for the main variables. Figure 1 shows the distributions of general knowledge, vocational knowledge, vocational practice, and GPA. Since the sample consists of individuals who successfully completed the apprenticeship, the distributions are concentrated above the passing threshold of 4.0. This is consistent with the Swiss grading scale, where grades of 4.0 or higher indicate sufficient performance, and with the qualification procedure, where passing generally requires at least a 4.0 in the practical examination and in the overall grade. Vocational knowledge grades are more dispersed and shifted somewhat to the left relative to the other grade measures.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	N
Panel A: Grades					
Vocational practice grade	4.83	0.44	4	6	16,487
Vocational knowledge grade	4.41	0.58	1	6	16,487
General knowledge grade	4.65	0.53	2	6	16,487
GPA	4.73	0.35	4	6	16,487
Panel B: Individual characteristics					
Age at exam	20.26	1.78	17	28	16,487
Female	0.44	0.50	0	1	16,487
Bridge-year program	0.16	0.36	0	1	16,487
Prior upper-secondary degree	0.07	0.25	0	1	16,487
Failed exam (first attempt)	0.06	0.25	0	1	16,487
Contract termination	0.21	0.41	0	1	16,487
VET as first choice	0.99	0.09	0	1	16,487
Panel C: Occupation characteristics					
Manual	0.51	0.50	0	1	14,417
Routine	0.11	0.31	0	1	14,417
Requirement level of occupation	39.95	9.74	14	62	15,290
Requirement level, mathematics	38.52	18.99	4	82	15,290
Requirement level, languages	52.26	14.78	19	83	15,290
Panel D: Labor market outcomes					
NEET (Year 1)	0.09	0.28	0	1	12,777
Earnings (Monthly, Year 1)	4253	998	585	7244	10,514
Tertiary entry (Year 1)	0.12	0.32	0	1	13,041
Stay with training firm	0.50	0.50	0	1	16,426

Notes: Earnings in Swiss francs (1 CHF ≈ 1 Euro ≈ 1.2 USD).

Figure 1: Distributions of the grades variables



Notes: The Swiss grading system ranges from 1.0 (lowest) to 6.0 (excellent). A score below 4.0 indicates failure, and while the system offers a wide range of grades that are not sufficient for passing, most of the low grades are rarely used.

Individuals in our sample are on average 20.3 years old and 44 percent of them are female. In the first year after graduation, average monthly earnings are CHF 4,253. 12 percent have entered tertiary education by the end of year 1, 50 percent stay with their training firm, and 9 percent are NEET in year 1.

2.4 Empirical strategy

Our empirical analysis studies how grade-based proxies for different dimensions of ability relate to early labor market outcomes. We identify the relationship between skill domains and early labor market outcomes by isolating the within occupation and cohort variation in individuals' grade-based measures.

A first set of specifications relates the overall GPA to the outcome Y_i:

$$Y_i = \alpha + \beta \, GPA_i + X_i'\gamma + \lambda_o + \delta_c + \varepsilon_i, \tag{1}$$

where GPA_i is the individual's overall grade point average, X_i is a vector of control variables, λ_o are occupation fixed effects, and δ_c are cohort fixed effects. The coefficient β captures the conditional relationship between overall ability and the outcome.

To examine which dimensions of ability/skill underlie the aggregate GPA gradient, we then replace GPA with the three grade components:

$$Y_i = \alpha + \beta_1 G_i + \beta_2 T_i + \beta_3 P_i + X_i'\gamma + \lambda_{o(i)} + \delta_{c(i)} + \varepsilon_i, \tag{2}$$

where G_i denotes general knowledge grades, T_i vocational knowledge grades, and P_i vocational practice grades. Estimating all three components jointly makes it possible to assess whether one domain contains predictive information for labor market outcomes beyond the other two.

The identifying variation therefore comes from differences in grades across individuals within the same occupation and cohort, conditional on observed background characteristics. This is central to our setting. Because training content and grading are standardized within each occupation through its national educational ordinance, the occupation fixed effects λ_o absorb systematic cross-occupational differences in grading standards, earnings levels, skill requirements, and post-training career paths. Cohort fixed effects δ_c further absorb common time-specific influences, including cohort-wide labor market conditions. The remaining variation reflects how individuals are graded relative to others trained and examined under the same occupational standard.

The vector of covariates X_i is measured prior to the qualification examination and therefore cannot be an outcome of grade performance. It includes age, gender, migration background (birthplace and nationality), urbanicity of residence, prior lower-secondary school track, whether the individual held an upper-secondary qualification before the apprenticeship, whether a bridge-year program was attended, whether the apprenticeship involved an occupational or employer change, and whether the qualification was completed on the first attempt.

For earnings, equations (1) and (2) are estimated by OLS. For binary outcomes such as NEET status, transition into tertiary education, and retention by the training firm, we use linear probability models, which allow for a straightforward comparison of coefficients across specifications and outcomes.

The estimates should be read as conditional associations. The results therefore identify which skill domains are most strongly related to early labor market outcomes, not the causal return to higher grades.

3 Skills and labor market outcomes

This section examines how achievement in vocational training relates to early labor market outcomes. We begin, in Subsection 3.1, with overall grade performance, which establishes a clear relation but cannot reveal which dimension of skill drives it. Subsection 3.2 therefore disaggregates the GPA into its three components and shows that the gradient is accounted for primarily by vocational practice skills, the dimension most directly tied to the tasks workers are trained to perform.

3.1 The relationship between overall GPA and labor market outcomes

The overall GPA, defined as the weighted average of all recorded grades, is a concise summary of achievement across the examination components and a natural benchmark for whether vocational-training skills predict labor market success. GPA may shape labor market entry by serving as an observable productivity signal when employers have limited information (Hansen et al., 2024; Landaud et al., 2026; Piopiunik et al., 2020), and, relative to the dichotomous completion measures common in much of the literature, it captures differences in achievement among graduates rather than only between graduates and non-completers (Mohrenweiser et al., 2020). We treat this aggregate relationship not as a finding in its own right, but as the benchmark we decompose in Section 3.2.

The raw relationship between GPA and early outcomes is clear and economically intuitive: higher grades are associated with a lower probability of being NEET one year after graduation, higher earnings, a higher probability of entering tertiary education, and a higher probability of remaining with the training firm (Figure 5 in Appendix C). These bivariate patterns are purely descriptive and do not account for compositional differences across individuals, occupations, or cohorts, but they already suggest that overall training performance is closely related to subsequent success.

Table 2 shows that these patterns persist once the covariates are included. GPA is negatively associated with NEET status and positively associated with earnings, transitions into tertiary education, and staying with the training firm, with all coefficients significant at the 1% level. The associations are therefore not only descriptively apparent but robust to conditioning on a rich set of observed characteristics.

Table 2: GPA and labor market outcomes

	(1) NEET (Y1)	(2) Earnings (Y1)	(3) Tertiary (Y1)	(4) Stayer
GPA	-0.060***	295.537***	0.163***	0.152***
	(0.008)	(30.983)	(0.009)	(0.013)
Female	-0.034***	28.072	0.014*	-0.040***
	(0.008)	(28.308)	(0.008)	(0.012)
Age at exam	0.000	28.448***	-0.009***	0.001
	(0.002)	(7.846)	(0.002)	(0.003)
Prior upper-secondary degree	-0.016	137.114***	-0.025**	0.082***
	(0.011)	(39.743)	(0.012)	(0.019)
Contract termination	0.023***	-69.981***	-0.010	-0.090***
	(0.007)	(23.514)	(0.006)	(0.010)
Failed exam (first attempt)	-0.002	39.802	0.015*	-0.009
	(0.011)	(40.250)	(0.009)	(0.017)
Bridge-year program	0.027***	-92.784***	0.003	-0.032***
	(0.008)	(26.773)	(0.007)	(0.011)
VET as first choice	0.019	134.137	-0.001	0.111***
	(0.022)	(106.522)	(0.035)	(0.043)
Intercept	0.327***	1967.773***	-0.517***	-0.427**
	(0.086)	(305.908)	(0.086)	(0.215)
Lower-secondary track FE	✓	✓	✓	✓
Migration background FE	✓	✓	✓	✓
Urbanity of residence	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Mean of outcome	0.085	4252.746	0.118	0.498
Treatment effect (% of mean)	-70.3	6.9	138.5	30.5
Observations	12,777	10,514	13,041	16,426

Notes: Dependent variables: (1) NEET probability in year 1; (2) Effective earnings during year 1; (3) Probability of entering tertiary level in year 1; (4) Probability of staying with the training firm. Sample sizes vary by outcome; see Appendix Table 7. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

The magnitudes are economically meaningful. A 0.1-point increase in GPA is associated with a 0.6-percentage-point lower probability of being NEET (about 7% of the mean), an earnings increase of roughly CHF 30 (about 0.7%), a 13.8% higher probability of entering tertiary education, and a 3.1% higher probability of staying with the training firm. Taken together, the GPA gradient confirms that vocational training performance is strongly related to early labor market outcomes.

Because the GPA averages over assessment domains that may capture substantively different dimensions of skills, the overall gradient does not reveal information about the skill dimension(s) that drive the statistical associations. The next subsection therefore replaces GPA with its three underlying grade components.

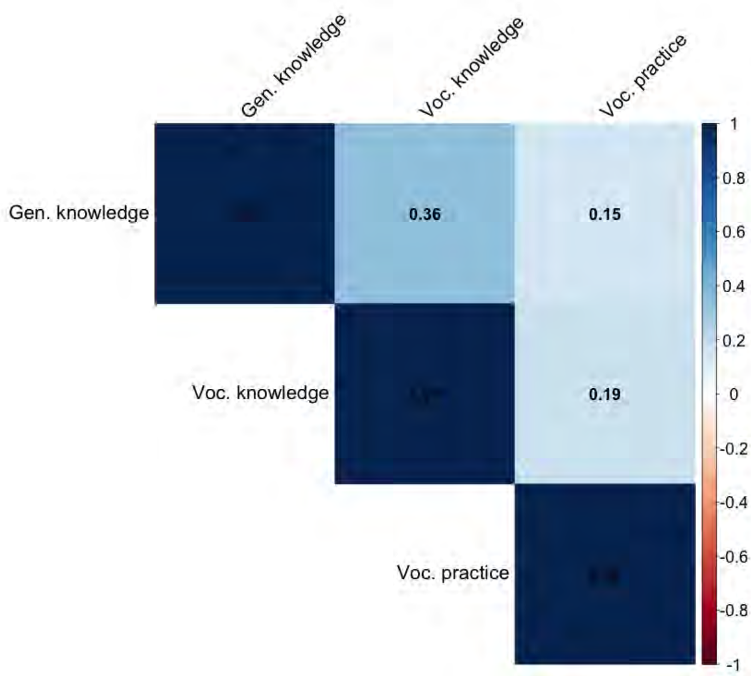
3.2 Skills dimensions

Recent work in the returns-to-skills literature emphasizes that labor-market-relevant competencies are multidimensional and that commonly used proxies often fail to capture occupation-specific or workplace-relevant competencies (Langer & Wiederhold, 2023; Piopiunik et al., 2020). We therefore decompose overall achievement into its three underlying domains and examine both how strongly these domains overlap and how each relates to subsequent labor market outcomes.

3.2.1 Similarity of the disaggregated skill measures

Figure 2 shows that the three grade components (general knowledge, vocational knowledge, and vocational practice) contain related but clearly non-identical information. The strongest association is between general knowledge and vocational knowledge grades (τ = 0.36), consistent with both resting on theory-oriented written or oral assessment. Vocational practice grades correlate positively with each of the other two, but only weakly, at around τ = 0.15 to τ = 0.19. All three correlations are low to moderate, so the components are far from collinear. Practical performance, in particular, captures a dimension of achievement that is only partially reflected in general knowledge or vocational knowledge grades.

Figure 2: Rank correlation between subgrades



Notes: Kendall rank correlation showing the similarity in ordering of the grades in ranking values: (-1,1). N = 16,487.

3.2.2 Theoretical and practical grades

To determine which skill dimensions account most for the aggregate GPA effects, Table 3 relates the three grade components to each labor market outcome, first entering them separately and then jointly.[2]

Table 3: Theoretical and practical grades and different outcomes

	(1)	(2)	(3)	(4)
Panel A: Grades and NEET (Year 1), N= 12,777				
Vocational practice	-0.040***			-0.035***
	(0.006)			(0.006)
Vocational knowledge		-0.019***		-0.008
		(0.005)		(0.006)
General knowledge			-0.020***	-0.009
			(0.006)	(0.007)
Panel B: Grades and earnings (Year 1), N= 10,514				
Vocational practice	192.876***			166.435***
	(22.818)			(23.943)
Vocational knowledge		106.363***		58.945***
		(18.478)		(20.468)
General knowledge			94.376***	33.480
			(22.465)	(24.678)
Panel C: Grades and Tertiary (Year 1), N= 13,041				
Vocational practice	0.071***			0.043***
	(0.007)			(0.007)
Vocational knowledge		0.070***		0.038***
		(0.005)		(0.006)
General knowledge			0.091***	0.063***
			(0.006)	(0.007)
Panel D: Grades and stayer, N= 16,426				
Vocational practice	0.126***			0.116***
	(0.009)			(0.010)
Vocational knowledge		0.044***		0.007
		(0.008)		(0.009)
General knowledge			0.061***	0.032***
			(0.009)	(0.010)
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓

Notes: Dependent variables: (A) NEET probability in year 1; (B) Effective earnings during year 1; (C) Probability of entering tertiary level in year 1; (D) Probability of staying with the training firm. Sample sizes vary by outcome; see Appendix Table 7. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

[2] All grades are issued on the same scale, so the coefficients of the non-standardized variables are already interpretable. However, Figure 1 shows that the grade distributions differ slightly. Appendix Table 8 therefore replicates the analysis with grades standardized to mean zero and standard deviation one; the results are qualitatively identical to Table 3, differing only in magnitude.

Columns (1) to (3) show that each grade domain is informative on its own: higher general knowledge, vocational knowledge, and vocational practice grades are each associated with a lower probability of being NEET one year after graduation, higher earnings, a higher probability of transitioning into tertiary education, and a higher probability of staying with the training firm.

The more informative specification is column (4), which enters all three grade domains jointly. A clear pattern emerges. Vocational practice grades remain significantly associated with all four outcomes: negatively with NEET status and positively with earnings, tertiary enrollment, and retention by the training firm. Vocational knowledge grades, by contrast, lose significance for NEET and retention, surviving only for earnings and tertiary education. General knowledge retains an independent relationship with tertiary education and retention; for most outcomes its coefficient is far smaller than that of vocational practice grades, the exception being tertiary education, where general knowledge is the strongest of the three. This pattern is consistent with broader academic achievement mattering most for the transition into further education.

Taken together, the results show that the aggregate GPA gradient is not driven equally by its components. Vocational practice performance accounts for the most robust part of the relationship between training performance and early labor market success, remaining significant across all four outcomes when the domains are entered jointly. General knowledge nonetheless retains an independent role, and an intuitive one: it is the strongest predictor of entry into tertiary education and is also related to lower NEET risk and to firm retention, suggesting that broader academic achievement captures abilities that matter for further education and for sustained labor market attachment.

3.3 Effect heterogeneity

Practical or tacit skills may be especially important in artisanal or manual occupations and less so in more cognitive ones (Autor & Handel, 2013; Autor et al., 2003). Likewise, because earnings growth is faster in non-routine occupations (Deming, 2025), the earnings return to practical skills may be larger there. Moreover, previous estimations could be driven by graduates who remain with their training firm. Stayers mechanically face a lower NEET risk, because continued employment is immediately available to them, and they may earn more if firms reward apprentices whose practical skills they have directly observed. Such a mechanism would still reflect a causal effect, but it would weaken the case for practical skills as a broadly valued dimension of human capital: the returns would operate largely within the training relationship rather than reflecting skills that the wider labor market recognizes and pays for.

To test for such differences, Table 4 reports subgroup-specific estimates for first-year earnings. Columns (1)–(4) split occupations by task content, manual versus cognitive and routine versus non-routine. Then, columns (5)–(6) split by gender, and columns (7)–(8) split by whether the graduate stays with or leaves the training firm.

The estimate for vocational practice grades is positive, sizable, and statistically significant in every subsample. Across the task-content and gender splits it ranges only from about 138 to 198 and clusters around the average effect of 166 reported in Table 3, so the earnings return to practical performance is not concentrated in a particular task type or gender. The point estimate is lower for women than for men, but the difference is not statistically significant in a two-sample Wald test ($p = 0.337$). General knowledge estimates, by contrast, are smaller and mostly insignificant across these splits.

The one dimension along which the practical premium differs is firm retention ($p = 0.062$). Among graduates who leave their training firm, the vocational practice estimate is nearly twice as large as among those who stay (about 187 versus 97), while leavers earn less on average (a mean of about 4,113 versus 4,393 CHF). This difference aligns with the findings reported by Mohrenweiser et al. (2020) and their asymmetric learning interpretation: the training firm has observed the apprentice directly throughout the apprenticeship, whereas an outside employer must infer practical ability largely from the certified grade, which should therefore carry more weight where direct information is scarcer. Tellingly, the gap is concentrated in the dimension of skill that is hardest to observe and to codify: for vocational practice the leaver premium is roughly double the stayer premium, whereas for general knowledge, the grade is unrelated to earnings in both groups. Moreover, the lower average earnings of leavers are consistent with models in which movers may be adversely selected on average (Altonji & Pierret, 2001; Farber & Gibbons, 1996; Gibbons & Katz, 1991; Schönberg, 2007). Because firms tend to retain the most productive apprentices, leaving immediately after graduation is seen as an adverse signal by recruiters. [3]

[3]We interpret these patterns descriptively. Because retention is itself an outcome predicted by the practical grade (Table 3), the stayer/leaver split conditions on a post-treatment variable and may also reflect selective mobility rather than employer information alone; separating signaling from productivity sorting is beyond what this design identifies.

Table 4: Grades and earnings (Year 1)

	(1) manual	(2) cognitive	(3) routine	(4) non-routine
Vocational practice	152.029***	178.078***	198.144***	152.514***
	(34.875)	(37.206)	(76.610)	(26.924)
Vocational knowledge	35.490	78.853**	-18.595	67.164***
	(29.687)	(36.026)	(63.528)	(24.407)
General knowledge	42.264	-28.864	-1.948	13.028
	(36.326)	(39.152)	(69.869)	(28.661)
Mean of outcome	4285.058	4292.290	4525.198	4257.004
Observations	5007	4053	1057	8003
	(5) female	(6) male	(7) stayer	(8) leaver
Vocational practice	137.793***	183.343***	96.578***	186.840***
	(33.562)	(33.600)	(30.168)	(37.868)
Vocational knowledge	54.930*	73.030***	29.765	88.911***
	(31.432)	(26.939)	(25.469)	(31.725)
General knowledge	-22.978	53.225	34.467	19.232
	(37.231)	(33.069)	(30.095)	(39.453)
Mean of outcome	4153.648	4324.735	4392.619	4112.999
Observations	4424	6090	5287	5195
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓

Notes: Subsample (linear) regressions on the subsamples characterized by the title of the column. Dependent variable: Effective earnings during year 1. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

Appendix Tables 9, 10, and 11 repeat the exercise for NEET status, tertiary education, and retention by the training firm. The results are broadly consistent with the main findings: across all three outcomes, vocational practice grades point in the expected direction in every subsample, predicting lower NEET probability, higher tertiary entry, and higher retention. Notably, for NEET and tertiary education the stayer and leaver estimates are almost identical (for NEET, −0.029 versus −0.034; for tertiary, 0.042 versus 0.047), so the larger leaver coefficient documented for earnings does not extend to the other outcomes, hence the retention-related heterogeneity is specific to earnings. General knowledge and vocational knowledge estimates vary somewhat more across outcomes and subsamples, but the broad pattern matches the average effects in Table 3. Taken together, the heterogeneity analysis indicates that the main findings are not driven by a particular occupational task group, by gender, or by retention status — with the single exception of the earnings premium, which is concentrated among graduates who change employers.

3.4 The predictive value of a practical skill measure

The regressions so far establish that practical performance is associated with early labor market outcomes. But does the practical grade carry information that is genuinely useful for predicting these outcomes, beyond what is already contained in a worker's background characteristics? To answer this, we move from explanatory associations to out-of-sample prediction.

Appendix Section D details the methodology. For each outcome, we conduct repeated out-of-sample prediction exercises, comparing a naive mean benchmark, a baseline specification, and specifications that separately add GPA or one of the three grade dimensions. Performance is evaluated using repeated 5-fold cross-validation, mean absolute error, and out-of-sample R^2. We complement this with random-forest permutation importance measures to rank variables by their contribution to predictive accuracy. Both exercises are descriptive and assess the predictive relevance of practical skills.

The results in Appendix Section D show that adding vocational practice grades improves out-of-sample predictive performance relative to the baseline for all four outcomes, in terms of both higher out-of-sample R^2 and lower mean absolute error. The improvement is most pronounced for earnings and retention by the training firm, where vocational practice grades predict at least as well as, and often better than, GPA, general knowledge, or vocational knowledge grades. For NEET status they improve on the baseline and perform similarly to GPA, while for transitions into tertiary education general knowledge and GPA are the strongest predictors, with vocational practice grades still adding content. The random-forest permutation-importance results reinforce this ordering: vocational practice grades rank among the most important predictors for earnings, NEET status, and retention, whereas general knowledge dominates for tertiary education. The two exercises ask different questions (incremental out-of-sample fit versus overall predictive contribution) but agree on the substantive point: the practical-skill measure carries information about early labor market outcomes beyond standard background characteristics, and as much as or more than any other single grade dimension for the labor market outcomes most central to this paper.

4 Skill composition and practical specialization

The previous section showed that vocational practice performance is systematically related to early labor market outcomes, even conditional on general knowledge and vocational knowledge achievement. Those additive specifications isolate the association of each grade domain, but they do not describe how the domains combine within an individual's skill profile. They cannot tell us, for instance, whether relative practical strength compensates for weaker theoretical performance, or whether two individuals with the same overall GPA fare differently depending on how their skills are composed. These are questions about relative standing that a model entering each grade separately is not designed to answer.

To address this, we proceed in two complementary steps. First, we use K-means clustering to identify recurring performance profiles without imposing ex-ante thresholds. This yields interpretable group comparisons and allows the three grade dimensions to combine nonlinearly. Second, we use principal component analysis to separate common overall performance from theoretical–practical orientation on a continuous scale. This exploits variation across the full grade distribution and allows us to ask whether relative practical orientation is related to outcomes beyond the boundaries of the discrete performance profiles.

4.1 Performance profiles and labor market outcomes

We start from three standardized grade measures that capture distinct dimensions of performance in vocational education: general knowledge (G), vocational knowledge (T), and vocational practice (P). To uncover latent "performance types" without imposing ex-ante thresholds, we apply K-means clustering to the grade triplet $x_i = (\mathrm{G}_i, \mathrm{T}_i, \mathrm{P}_i) \in \mathbb{R}^3$. The K-means objective partitions the sample into K groups and chooses centroids $\{\mu_k\}_{k=1}^{K}$ to minimize within-cluster dispersion,

$$\min_{\{c(i)\},\{\mu_k\}} \sum_{i=1}^{N} \left\| x_i - \mu_{c(i)} \right\|^2, \tag{3}$$

where $c(i) \in \{1, \ldots, K\}$ denotes the cluster assignment and $\| \cdot \|$ is the Euclidean norm. Computationally, the algorithm iterates between (i) assigning each observation to its nearest centroid and (ii) updating each centroid to the mean of observations assigned to that cluster until the objective in (3) no longer improves (Hartigan & Wong, 1979). This type of data-driven discretization of heterogeneity is closely related to approaches used in modern labor economics to obtain interpretable "types", e.g., grouping firms or workers into classes before studying outcomes or sorting patterns (Böhm et al., 2025; Bonhomme & Manresa, 2015; Bonhomme et al., 2019). The resulting groups summarize recurring combinations across the three grade domains and provide an interpretable way to compare apprentices with different skill profiles.

Table 5: Cluster profiles

	Cluster 1 (C1) Practitioner	Cluster 2 (C2) Theoretician	Cluster 3 (C3) Overperformer	Cluster 4 (C4) Underperformer
Vocational practice	0.72 (0.55)	-0.84 (0.57)	0.85 (0.67)	-0.74 (0.67)
Vocational knowledge	-0.30 (0.66)	0.22 (0.66)	1.02 (0.62)	-1.07 (0.74)
General knowledge	-0.38 (0.75)	0.34 (0.62)	0.94 (0.60)	-1.04 (0.77)
GPA	4.77 (0.18)	4.64 (0.19)	5.15 (0.20)	4.32 (0.19)
Age at exam	20.23 (1.74)	20.27 (1.74)	20.10 (1.73)	20.47 (1.90)
Female	0.45 (0.50)	0.44 (0.50)	0.51 (0.50)	0.37 (0.48)
Bridge-year program	0.16 (0.37)	0.15 (0.36)	0.11 (0.32)	0.21 (0.41)
Prior upper-sec. degree	0.07 (0.26)	0.05 (0.22)	0.05 (0.21)	0.11 (0.31)
Failed exam (first attempt)	0.05 (0.22)	0.07 (0.25)	0.01 (0.11)	0.14 (0.34)
Contract termination	0.21 (0.40)	0.22 (0.41)	0.18 (0.39)	0.26 (0.44)
Manual	0.45 (0.50)	0.55 (0.50)	0.55 (0.50)	0.49 (0.50)
Routine	0.12 (0.32)	0.09 (0.29)	0.14 (0.35)	0.08 (0.28)
NEET (Year 1)	0.08 (0.26)	0.10 (0.30)	0.06 (0.24)	0.11 (0.31)
Earnings (Monthly, Year 1)	4319 (960)	4238 (1035)	4326 (958)	4131 (1019)
Tertiary entry (Year 1)	0.11 (0.31)	0.10 (0.31)	0.20 (0.40)	0.04 (0.21)
Stay with training firm	0.53 (0.50)	0.47 (0.50)	0.54 (0.50)	0.45 (0.50)
N	4184	4496	4124	3683

Notes: Means and standard deviations (in parentheses). Method: k-means clustering with k = 4 clusters. N = 16,487. Missing policy: complete cases on cluster variables only (descriptive covariates may have NA). Scaling: z-scored globally (on the used sample).

The data-driven solution reported in Table 5 yields four clearly interpretable groups. *Overperformers* (Cluster 3) score well above average in all three grade domains, and *Underperformers* (Cluster 4) below average in all three. The two intermediate groups are near mirror images in the *composition* of their performance: *Theoreticians* (Cluster 2) sit around average in general knowledge and vocational knowledge but clearly below average in vocational practice, whereas *Practitioners* (Cluster 1) are comparatively strong in vocational practice and somewhat weaker in the two theory-oriented domains. These labels are purely descriptive and summarize only the relative profiles implied by the unsupervised cluster centroids.

The key contrast for our purpose is between Practitioners and Theoreticians, because the two differ far more in the composition of their skills than in their overall level. Their average GPAs are close (4.77 versus 4.64), yet they lean in opposite directions: Practitioners toward practice, Theoreticians toward general and theoretical knowledge. This makes the comparison a direct test of whether a practice-oriented profile is associated with different early labor market outcomes than a theory-oriented one, holding overall performance roughly fixed.

The cluster profiles differ in meaningful ways beyond the three grade dimensions. Indicators of the training trajectory and early outcomes line up closely at the extremes: Underperformers are more likely to have completed a bridge year, to hold a previous degree, and to have failed the final qualification, and they show the least favorable early outcomes, including the lowest retention rate, and the highest NEET incidence. Overperformers fare better both during and after training.

The most striking group, however, is the Practitioners. Their overall GPA (4.77) is well below that of the Overperformers (5.15) and only moderate in absolute terms, yet they record the second highest average first-year earnings of any cluster (CHF 4,319, just slightly below the Overperformers' CHF 4,326) and the second-highest retention rate, with lower NEET incidence than both Theoreticians and Underperformers. A practice-oriented profile thus appears to compensate, in the labor market, for an unexceptional GPA.[4]

Table 6: Performance profiles and labor market outcomes

	(1) NEET (Year 1)	(2) Earnings (Year 1)	(3) Tertiary (Year 1)	(4) Stayer
Practitioner	-0.023***	79.926***	-0.006	0.063***
	(0.007)	(25.971)	(0.008)	(0.011)
Theoretician	Ref.	Ref.	Ref.	Ref.
Overperformer	-0.037***	138.223***	0.089***	0.087***
	(0.007)	(26.267)	(0.008)	(0.011)
Underperformer	0.006	-80.657***	-0.040***	-0.039***
	(0.008)	(28.171)	(0.007)	(0.012)
Intercept	0.048	3337.372***	0.251***	0.290
	(0.073)	(268.946)	(0.075)	(0.207)
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Mean of outcome	0.085	4252.746	0.118	0.498
Observations	12,777	10,514	13,041	16,426

Notes: Theoreticians are the reference group ('Ref.'). Dependent variables: (1) NEET probability in year 1; (2) Effective earnings during year 1; (3) Probability of entering tertiary level in year 1; (4) Probability of staying with the training firm. Sample sizes vary by outcome; see Appendix Table 7. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

Table 6 examines whether these differences survive conditioning on the full set of covariates, occupation fixed effects, and cohort fixed effects. Theoreticians serve as the reference group, so the Practitioner coefficient captures the outcome difference between a relatively practice-oriented and a relatively theory-oriented profile within the same occupation and cohort. The advantage persists: relative to Theoreticians, Practitioners earn monthly about CHF 80 more in the first year, are 2.3 percentage points less likely to be NEET, and are 6.3 points more likely to stay with the

[4]Table 5 shows that these differences are not mirrored by large differences in observed occupational characteristics: average occupation-level measures such as manual and routine task content differ only modestly across clusters. The cluster differences therefore do not merely reflect sorting into different occupations, but capture heterogeneity in performance profiles within the vocational training system.

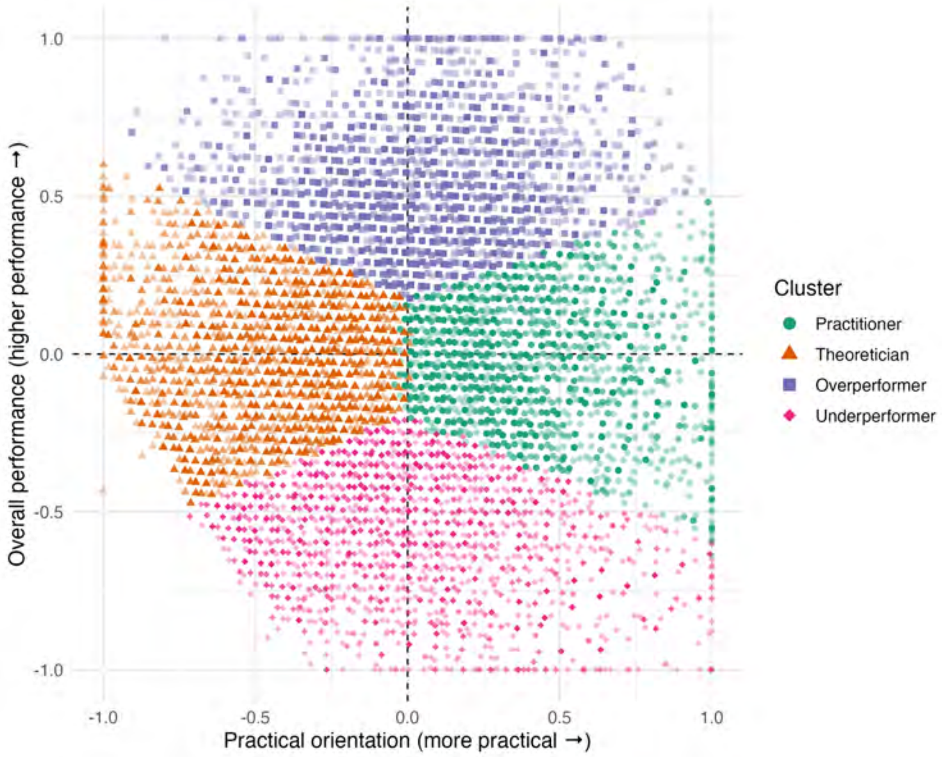
training firm. The one exception is entry into tertiary education, where the two groups do not differ — consistent with the earlier finding that further education is tied to general knowledge rather than to practical performance. Aggregate GPA thus masks substantively different skill profiles with different labor market relevance: a more practice-oriented profile is associated with better early labor market outcomes than a theory-oriented one, even when overall GPA is not exceptional.

4.2 Overall performance and theoretical–practical orientation

The cluster analysis identifies recurring performance profiles and provides an intuitive comparison between Practitioners and Theoreticians. It does not, however, provide a continuous measure of how strongly an individual's performance profile leans toward theoretical or practical strength, nor does it directly separate this orientation from the individual's overall performance level. A continuous representation allows us to see whether the two dimensions act as complements, that is, whether the return to practical strength depends on a worker's overall performance. Whether distinct skill dimensions reinforce one another is theoretically ambiguous and empirically mixed: Iversen et al. (2016) find that schooling and wage-work experience are complementary inputs in the earnings function of entrepreneurs, though the complementarity is absent for wage-employed workers, while Deming (2017) documents a complementarity between cognitive and social skills but not between cognitive skills and other non-cognitive measures. We therefore interact our two continuous dimensions and test for such a complementarity directly.

We construct two continuous indices using principal component analysis (PCA) applied to the same standardized grade vector x_i (Jolliffe, 2002). PCA finds orthogonal directions (loadings) $v_1, v_2, \ldots$ that successively maximize the variance of the projected data. Equivalently, if $\widehat{\Sigma}$ denotes the sample covariance (or correlation) matrix of x_i, PCA solves the eigen-decomposition $\widehat{\Sigma} v_j = \lambda_j v_j$ with $\lambda_1 \geq \lambda_2 \geq \cdots$, and the component scores are the projections $s_{ij} = v_j' x_i$. We use the first two components to define two indices. *Overall performance* loads similarly on G, T, and P and therefore captures common, overall performance. *Practical orientation* loads positively on P and negatively on G and T, and therefore captures relative practical (versus theoretical) strength; higher values denote a more practice-oriented profile. We plot each individual in the (Practical orientation, Overall performance) plane in Figure 3, coloring points by K-means cluster membership to make the link between the discrete types and the continuous skill structure transparent.

Figure 3: Individual performance in the (Practical orientation, Overall performance) plane.

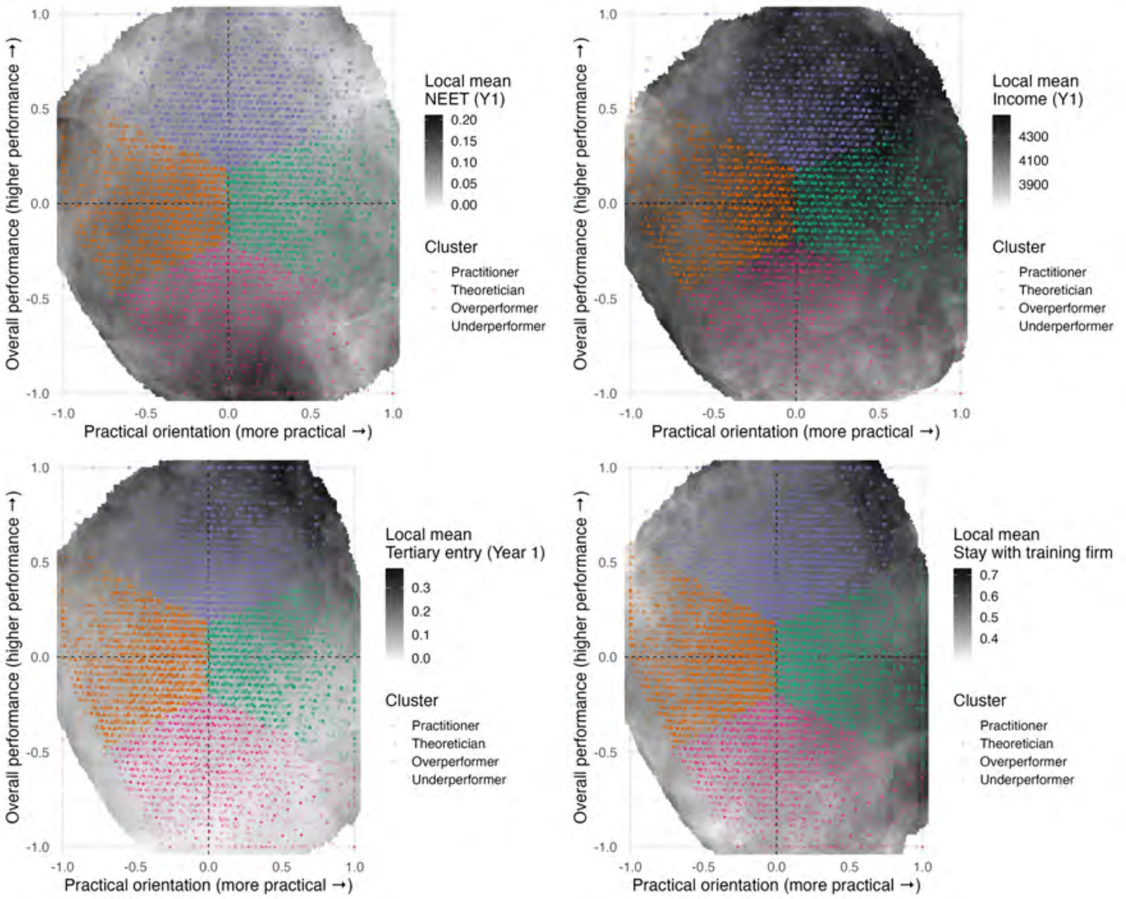


Higher practical orientation reflects stronger practical relative to theoretical performance; higher overall performance reflects higher grades in all three domains, both dimensions calculated with the PCA approach described in the text. The cluster membership is based on the k-means clustering shown in Table 5.

Figure 3 shows the two PCA dimensions, overall performance on the y-axis and practical orientation on the x-axis, with cluster membership indicated by color and shape. The overall performance component primarily orders apprentices by their level of performance in all three dimensions: Overperformers concentrate toward the top of the graph and Underperformers toward the bottom. Practical orientation, by contrast, separates relative practical from theoretical strength: Practitioners concentrate on the right, practice-oriented side, and Theoreticians on the left, theory-oriented side. At the same time, the continuous representation retains substantial variation within each performance profile, allowing us to study whether practical orientation is related to outcomes across the full grade distribution rather than only through comparisons between discrete groups.

Figure 4 provides a descriptive view of how the two skill dimensions relate to the four main outcomes. The colored points show the four clusters in the same PCA space as before, while the grey background reports local outcome means at each point. The figure thus reveals whether outcome differences are driven mainly by the overall level of performance (the vertical dimension) or by the relative orientation toward practical versus theoretical skill (the horizontal dimension).

Figure 4: Individual performance and different outcomes



Higher practical orientation reflects stronger practical relative to theoretical performance; higher overall performance reflects higher grades in all three domains. Background shading shows local means of the following outcomes: NEET probability in year 1 (top left), effective earnings during year 1 (top right), probability of entering tertiary level in year 1 (bottom left), and probability of staying with the training firm by the end of year 0 (bottom right). Local means are calculated for each point in the graph using all observations within a radius of 0.25, with a minimum of 50 observations per radius.

The two dimensions sort the outcomes cleanly. NEET status and transitions to tertiary education vary along the *vertical* dimension: NEET is concentrated among low-overall-performance individuals at the bottom of the graph, and tertiary education entry among high-performance individuals at the top, with little horizontal variation. Earnings and staying, by contrast, display a pronounced *horizontal* gradient: holding overall performance fixed, local means improve toward the practice-oriented (right) side of the graph. This visual pattern mirrors the regression results: further education tracks overall and general knowledge performance, whereas labor market attachment and pay track practical orientation. The pattern thus shows that the relevance of practical orientation is not confined to a single discrete cluster but holds continuously across the grade distribution.

Appendix Table 12 reports the corresponding regression using the two continuous PCA dimensions. Higher overall performance is associated with more favorable outcomes throughout. Practical orientation adds a second, distinct gradient: conditional on overall performance, a more practice-oriented profile is associated with higher first-year earnings and a greater probability of remaining with the training firm, and with a lower probability of being NEET. It is unrelated to entry into tertiary education, consistent with further education tracking general rather than practical performance. The continuous estimates thus reproduce the cluster and heatmap patterns: overall level and practical orientation matter for different outcomes, and practical orientation is rewarded specifically in early labor market attachment and pay.

The two coefficients in Table 12 are not directly comparable to those in Table 3. Because the overall-performance index loads on all three domains, a one-unit increase corresponds to improving every grade simultaneously, whereas practical orientation captures a shift toward practice at the expense of theoretical performance. The positive orientation coefficient therefore indicates that practical grades carry greater weight than the theoretical components — the same conclusion as Table 3, expressed on a continuous scale.

The interaction between overall performance and practical orientation is small and statistically insignificant for all outcomes (Appendix Table 12). This null is consistent with Iversen et al. (2016), who likewise find no theory–practice complementarity among wage-employed workers, and adds to the evidence that complementarities between skill dimensions are pair- and context-specific rather than universal.

5 Conclusion

Despite decades of theoretical work emphasizing the importance of tacit knowledge and practical skills for productivity, empirical labor economics has lacked direct measures of this dimension of human capital. This paper helps fill that gap by exploiting a unique institutional feature of the Swiss apprenticeship system that generates standardized assessments of authentic occupational performance for the full population of vocational graduates. By linking these assessments to rich administrative records on educational histories and early labor market careers, we examine how revealed practical skills relate to subsequent labor market outcomes while accounting for detailed information on other dimensions of human capital.

Our findings suggest that revealed practical skills constitute a distinct dimension of human capital that is only imperfectly captured by conventional educational measures. Although practical performance is positively associated with both general knowledge and vocational knowledge, these correlations are modest, indicating that the three examination components measure different aspects of worker capability. Revealed practical skills emerge as the most consistent predictor of labor market success at the beginning of workers' careers, remaining significantly associated with all outcomes we consider: higher earnings, a lower probability of becoming NEET, higher retention by the training firm, and a greater likelihood of entering tertiary education. By contrast, vocational knowledge loses much of its explanatory power once practical skills and general knowledge are taken into account, retaining an independent association only with earnings and tertiary entry. General knowledge is most strongly related to continued educational participation, while also remaining independently associated with firm retention. Taken together, these results suggest that practical skills capture an economically meaningful source of worker heterogeneity that is largely overlooked by aggregate grades or more academic measures of achievement.

The observed relationships are consistent with two complementary economic mechanisms. Practical skills may directly enhance productivity because workers who perform occupational tasks more effectively create greater value for employers. At the same time, certified practical performance may serve as a valuable signal in labor markets characterized by incomplete information. The stronger earnings association among graduates who change employers than among those who remain with their training firm is consistent with employer-learning models in which outside firms rely more heavily on observable credentials, whereas training firms have already acquired private information about workers' productive capacity (Altonji & Pierret, 2001; Farber & Gibbons, 1996; Gibbons & Katz, 1991). Although our empirical design does not identify the relative importance of these two channels, the evidence suggests that both productivity and signaling are likely to contribute to the labor market value of practical skills.

Our analysis is necessarily subject to several limitations. Most importantly, the available administrative data currently allow us to observe all cohorts only during the first year after graduation; longer earnings trajectories are available only for the earliest cohorts. Consequently, our analysis speaks primarily to labor market entry rather than to longer-run career dynamics. In addition, the estimated relationships remain conditional associations and may still reflect unobserved worker or firm characteristics despite the unusually rich set of administrative controls available in our data.

Beyond these specific results, our findings suggest that labor economics may benefit from moving beyond the traditional distinction between cognitive and non-cognitive skills toward a richer characterization of occupation-specific practical human capital. Many economically valuable skills are acquired not through classroom instruction but through repeated performance of authentic work tasks under supervision and feedback. Such skills have historically been difficult to measure at scale and have therefore remained largely absent from empirical analyses of labor market success. Our results indicate that this omission is consequential.

Relatedly, our findings suggest that the measurement of human capital deserves at least as much attention as its estimation. Since Becker (1964), labor economics has devoted considerable effort to understanding how human capital is accumulated and rewarded, yet comparatively little attention has been paid to how different dimensions of human capital are actually revealed. Our results indicate that practical skills become visible primarily through the execution of authentic occupational tasks under real working conditions. In contrast, assessments based on written examinations, or even performance in stylized or simulated settings, may reveal only part of the practical capabilities that employers value. This observation resonates with Miller's (1990) influential framework of competence assessment, which distinguishes between what individuals know, what they know how to do, what they can demonstrate under test conditions, and what they actually do in authentic professional settings. Our findings suggest that economically valuable practical skills are revealed most fully in authentic performance settings. As educational systems increasingly seek to assess practical competencies, greater attention should therefore be paid not only to what is measured, but also to how it is measured.

Finally, the importance of measuring practical skills may become even greater as technological change reshapes the nature of work. Advances in artificial intelligence increasingly substitute for tasks based on codified knowledge while potentially increasing the relative importance of capabilities that require the execution, adaptation, and transmission of occupation-specific know-how. At the same time, remote work and automation may weaken the workplace interactions through which practical knowledge has traditionally been transferred from experienced workers to novices (Brynjolfsson et al., 2025; Ide, 2025; Lambert & Schindler, 2026). Understanding how practical skills are accumulated, certified, and rewarded therefore represents an important agenda not only for future labor economics research, but also for the design of education and training systems.

References

Altonji, J. G., & Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. *The Quarterly Journal of Economics*, *116*(1), 313–350. https://doi.org/10.1162/003355301556329

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies*, *29*(3), 155–173. https://doi.org/10.2307/2295952

Autor, D. H., & Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, *31*(S1), S59–S96. https://doi.org/10.1086/669332

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Bartelsman, E., Dobbelaere, S., & Mattioli, A. Z. (2024). *Non-compete Agreements, Tacit Knowledge and Market Imperfections*. IZA - Institute of Labor Economics. Retrieved June 3, 2026, from https://www.jstor.org/stable/resrep69217

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. The University of Chicago Press.

Böhm, M. J., Esmkhani, K., & Gallipoli, G. (2025). Firm heterogeneity in skill returns. *Journal of Labor Economics*, *43*(3), 695–723. https://doi.org/10.1086/729103

Bonhomme, S., Lamadon, T., & Manresa, E. (2019). A distributional framework for matched employer–employee data. *Econometrica*, *87*(3), 699–739. https://doi.org/10.3982/ECTA15722

Bonhomme, S., & Manresa, E. (2015). Grouped patterns of heterogeneity in panel data. *Econometrica*, *83*(3), 1147–1184. https://doi.org/10.3982/ECTA11319

Brynjolfsson, E., Chandar, B., & Chen, R. (2025, November). *Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence*. Stanford Digital Economy Lab. https://digitaleconomy.stanford.edu/publications/canaries-in-the-coal-mine/

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, *69*(5), 1127–1160.

Cianciolo, A. T., Grigorenko, E. L., Jarvin, L., Gil, G., Drebot, M. E., & Sternberg, R. J. (2006). Practical intelligence and tacit knowledge: Advancements in the measurement of developing expertise. *Learning and Individual Differences*, *16*(3), 235–253. https://doi.org/10.1016/j.lindif.2006.04.002

Cingano, F. (2003). Returns to specific skills in industrial districts. *Labour Economics*, *10*(2), 149–164. https://doi.org/10.1016/S0927-5371(03)00005-8

Cnossen, F., Piracha, M., & Tchuente, G. (2025). Learning the Right Skill: Vocational Curricula and Returns to Skills. *Journal of Labor Economics*, *43*(3), 665–694.

Cowan, R., David, P. A., & Foray, D. (2000). The explicit economics of knowledge codification and tacitness. *Industrial and Corporate Change*, *9*(2), 211–253. https://doi.org/10.1093/icc/9.2.211

De La Croix, D., Doepke, M., & Mokyr, J. (2018). Clans, Guilds, and Markets: Apprenticeship Institutions and Growth in the Preindustrial Economy. *The Quarterly Journal of Economics*, *133*(1), 1–70. https://doi.org/10.1093/qje/qjx026

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593–1640. https://doi.org/10.1093/qje/qjx022

Deming, D. J. (2025). Why do Wages Grow Faster for Educated Workers? *Journal of Labor Economics*. https://doi.org/10.1086/737990

Deming, D. J., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, *36*(S1), S337–S369.

Deming, D. J., & Silliman, M. (2025). Skills and human capital in the labor market. In C. Dustmann & T. Lemieux (Eds.), *Handbook of Labor Economics* (pp. 115–157, Vol. 6). Elsevier. https://doi.org/10.1016/bs.heslab.2025.07.001

Dorn, D., Schoner, F., Seebacher, M., Simon, L., & Woessmann, L. (2025). *Multidimensional skills on LinkedIn profiles: Measuring human capital and the gender skill gap*. CESifo Working Paper.

Dustmann, C., & Meghir, C. (2005). Wages, Experience and Seniority. *The Review of Economic Studies*, *72*(1), 77–108. https://doi.org/10.1111/0034-6527.00325

Eggenberger, C., Rinawi, M., & Backes-Gellner, U. (2018). Occupational specificity: A new measurement based on training curricula and its effect on labor market outcomes. *Labour Economics*, *51*, 97–107.

Farber, H. S., & Gibbons, R. (1996). Learning and Wage Dynamics. *The Quarterly Journal of Economics*, *111*(4), 1007–1047. https://doi.org/10.2307/2946706

Foray, D. (2004). *Economics of Knowledge*. MIT Press.

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach. *Journal of Labor Economics*, *28*(1), 1–49.

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). *Journal of Economic Geography*, *3*(1), 75–99. https://doi.org/10.1093/jeg/3.1.75

Gibbons, R., & Katz, L. F. (1991). Layoffs and Lemons. *Journal of Labor Economics*, *9*(4), 351–380. https://doi.org/10.1086/298273

Hansen, A. T., Hvidman, U., & Sievertsen, H. H. (2024). Grades and employer learning. *Journal of Labor Economics*, *42*(3), 659–682. https://doi.org/10.1086/724048

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, *73*, 103–130. https://doi.org/10.1016/j.euroecorev.2014.10.006

Hartigan, J. A., & Wong, M. A. (1979). A K-means clustering algorithm. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *28*(1), 100–108. https://doi.org/10.2307/2346830

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482. https://doi.org/10.1086/504455

Howells, J. R. L. (2002). Tacit Knowledge, Innovation and Economic Geography. *Urban Studies*, *39*(5–6), 871–884. https://doi.org/10.1080/00420980220128354

Ide, E. (2025). *Automation, AI, and the Intergenerational Transmission of Knowledge*. https://doi.org/10.48550/ARXIV.2507.16078

Iversen, J., Malchow-Møller, N., & Sørensen, A. (2016). Success in entrepreneurship: A complementarity between schooling and wage-work experience. *Small Business Economics*, *47*(2), 437–460. https://doi.org/10.1007/s11187-016-9732-y

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer. https://doi.org/10.1007/b98835

Kelly, M., Mokyr, J., & Ó Gráda, C. (2014). Precocious Albion: A New Interpretation of the British Industrial Revolution. *Annual Review of Economics*, *6*(1), 363–389. https://doi.org/10.1146/annurev-economics-080213-041042

Kelly, M., Mokyr, J., & Ó Gráda, C. (2023). The Mechanics of the Industrial Revolution. *Journal of Political Economy*, *131*(1), 59–94. https://doi.org/10.1086/720890

Kiener, F., Gnehm, A.-S., Clematide, S., & Backes-Gellner, U. (2022). IT skills in vocational training curricula and labour market outcomes. *Journal of Education and Work*, *35*(6–7), 614–640.

Lambert, P. J., & Schindler, Y. (2026, May 18). *The Broken Ladder: AI, Remote Work, and Early-Career Hiring*. https://doi.org/10.2139/ssrn.6787638

Landaud, F., Maurin, É., Willage, B., & Willén, A. (2026). The value of a high school GPA. *Review of Economics and Statistics*, 1–9. https://doi.org/10.1162/rest_a_01422

Langer, C., & Wiederhold, S. (2023). *The value of early-career skills* (Working Paper No. 10288). CESifo. https://www.ifo.de/DocDL/cesifo1_wp10288.pdf

Lazear, E. P. (2009). Firm-Specific Human Capital: A Skill-Weights Approach. *Journal of Political Economy*, *117*(5), 914–940. https://doi.org/10.1086/648671

Lise, J., & Postel-Vinay, F. (2020). Multidimensional Skills, Sorting, and Human Capital Accumulation. *American Economic Review*, *110*(8), 2328–2376. https://doi.org/10.1257/aer.20162002

Miller, G. E. (1990). The assessment of clinical skills/competence/performance. *Academic Medicine*, *65*(9), S63–S67. https://doi.org/10.1097/00001888-199009000-00045

Mincer, J. A. (1974). *Schooling, experience, and earnings*. National Bureau of Economic Research.

Mohrenweiser, J., Wydra-Somaggio, G., & Zwick, T. (2020). Information advantages of training employers despite credible training certificates. *Oxford Economic Papers*, *72*(3), 651–671. https://doi.org/10.1093/oep/gpz052

Perraton, J., & Tarrant, I. (2007). What does tacit knowledge actually explain? *Journal of Economic Methodology*, *14*(3), 353–370. https://doi.org/10.1080/13501780701562559

Piopiunik, M., Schwerdt, G., Simon, L., & Woessmann, L. (2020). Skills, signals, and employability: An experimental investigation. *European Economic Review*, *123*, 103374. https://doi.org/10.1016/j.euroecorev.2020.103374

Rubinstein, Y., & Weiss, Y. (2006). Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning. In *Handbook of the Economics of Education* (pp. 1–67, Vol. 1). Elsevier. https://doi.org/10.1016/S1574-0692(06)01001-4

Schönberg, U. (2007). Testing for Asymmetric Employer Learning. *Journal of Labor Economics*, *25*(4), 651–691. https://doi.org/10.1086/522905

SERI. (2019). *Orientierungshilfe für die Ausgestaltung der Qualifikationsverfahren mit Abschlussprüfung*. State Secretariat for Education, Research and Innovation. Bern.

Sternberg, R. J. (1985). *Beyond IQ: A Triarchic Theory of Human Intelligence*. CUP Archive.

Streeck, W. (2011). *Skills and politics. General and specific* (Working Paper No. 11/1). MPIfG Discussion Paper. Retrieved May 26, 2026, from https://www.econstor.eu/handle/10419/45624

Wagner, R. K. (2011, May 30). Practical Intelligence. In R. J. Sternberg & S. B. Kaufman (Eds.), *The Cambridge Handbook of Intelligence* (1st ed., pp. 550–563). Cambridge University Press. https://doi.org/10.1017/CBO9780511977244.028

Appendices

A Examples of practical works

This appendix provides concrete examples of the vocational practice component across occupations, to illustrate what the practical grade measures. Two features stand out. First, the assessments are substantial and occupation-specific: they range from a six-hour exercise for Hospitality Services Specialists to individual projects of 64–104 hours for Electronics Technicians, each defined by the occupation's own training ordinance. Second, the grade reflects more than a finished product. Across occupations, the rubric weights the methodology and results of the work, accompanying documentation, a presentation, and a technical discussion with the experts, so that candidates are assessed on how they plan, execute, document, and explain real tasks rather than on a single output.

A.1 Electronics Technician (ID 46506, 4 years)

The individual practical work for the Electronics Technician, lasting 64–104 hours, consists of four parts.

1. Methodology and results of the work (60%)
2. Documentation (10%)
3. Presentation (10%)
4. Expert discussion (20%)

Example of an individual practical work for a communication firm:

The project is an extension of the existing code lock (CS), which is designed to switch a video surveillance system on and off. The CS is controlled by a SAB 80C537-N microprocessor and operated via a 3x4-button membrane keypad. A 16x2 character dot matrix display is used for the display. The aim is now to enable digital control of the contrast and backlighting on this display. To this end, a menu is to be programmed that allows the user to operate the system as easily as possible.

Menu functions to be programmed

- Contrast: increase or decrease the contrast using buttons 4 (-) and 6 (+).
- Backlight: switch on and off.
- Backlight brightness: increase or decrease the backlight brightness using buttons 4 (-) and 6 (+). This only applies if AutoBacklight is switched off.
- AutoBacklight: automatically and continuously adjusts the backlight intensity to the ambient light level.

- AutoBacklightOff: automatically switches off the backlight after a certain period following the last key press (switch on and off).

Technical requirements

- The analog voltages for contrast and backlighting are to be generated using an X9C102 (digitally controllable potentiometer).
- A suitable LDR is to be selected to measure ambient light levels.
- The prototype is to be built on a separate circuit board, as there is no more space available on the existing one. A 20-pin D-Sub cable is used for the connection.
- The program for generating the menu should contain as few commands as possible. The connection to the existing program is made via an UP call.

A.2 Hospitality Services Specialist (ID 78404, 3 years)

The practical work for Hospitality Services Specialists, lasting six hours, consists of two parts.

1. Expert discussion of 30 minutes, with 5 minutes preparation time. The expert discussion will address issues relating to all areas of professional competence, defined in the curricula. Example questions
   - The clinic's philosophy is 'Back to everyday life in good health'. How do you incorporate this into your communication and behavior?
   - What role do your body language and tone of voice play when dealing with bedridden patients? How do you adapt them?
   - How do you respond if, whilst on duty, you notice that a hygiene regulation has not been followed? Describe how you handle this situation
   - What alternatives would you suggest if a guest declines the meat dish? Explain your recommendation.
   - A guest asks for a recommendation for a drink that aids recovery. How would you proceed?
   - How do you organize the serving process when the food is delivered in a heated trolley? Which hygiene considerations are particularly important?
2. The assigned practical work, in two areas:
   (a) Presentation and communication; Serving food and drink (30%). Example assignment:
      - Mrs Weber was involved in a cycling accident and has been in the rehabilitation clinic for three weeks. She is due to be discharged on 30 August. On 20 August, Mrs Weber is celebrating her 40th birthday. Mr Weber would like to surprise his wife with a lunch at your rehabilitation clinic. A total of 12 people, including 3 children (aged 11, 10 and 7), are expected. Plan this event.
        – Create a menu for the planned three-course meal, including a vegetarian option and a selection of two alcoholic and two non-alcoholic drinks (hot and cold). 20 minutes
        – Set the sample table for six people in accordance with your menu, including decoration. The decoration must consist of at least three different elements. 15 minutes

    - Welcome Mr and Mrs Weber and escort them to their table. 3 minutes
    - Present the menu and the drinks selection, and tailor your recommendations to the guests' needs. Take the dessert orders. 12 minutes
    - Prepare the requested drinks. Then serve the couple their chosen drinks and respond to their requests. 15 minutes Whilst preparing the drinks, you notice that they are not cold enough. You check the temperature and arrange for the drinks cooler to be repaired. 15 minutes
    - After lunch, Mr and Mrs Weber and their children would like to reserve a table for lunch on the day of Mrs Weber's discharge. 10 minutes

(b) Cleaning and tidying rooms; Ensuring the supply of linen; Organizing and implementing operational procedures (50%). Example assignment:

- You are working at Reference Firm 2 and have been tasked with cleaning and preparing the 'Moléson' meeting room for an event. As the person responsible for cleaning, you are also responsible for instructing the trainees.
    - Carry out routine cleaning of the 'Moléson' meeting room.
    - Prepare this room in accordance with the customer's requirements, using the booking form.
    - Decorate the meeting room with the bouquet/arrangement/decoration requested by the customer and designed by you.
    - Instruct a student studying for a qualification in Hospitality Services Specialist on how to clean the corridor floor using the scrubber-dryer.

A.3 Carpenter (ID 30303, 4 years)

The practical work lasts 16 hours, and consists of

1. Exam items on preparation of work (25%)
2. Exam items on curing of structural components, erecting timber structures (25%)
3. Prefabrication of components; installation of protective coatings and insulation; fitting of cladding / substructures; installation of prefabricated products (50%)

Below is an example of a pre-fabricated component. For the third part of the examination, candidates must build a total of 4–5 such structures.

- Assignment: Create the floor grating as an element with cut-outs for the stairs.
- Details: Floor grating boards: planed spruce, 24/100 mm
- Substructure joists: planed spruce, 24 mm thick (dimensions 24/25 or 24/50 mm). The floor grating boards are screwed into place from above, so that the screws are visible. The edges of the boards and joists must be neatly finished.
- Equipment: hand tools, hand-held power tools
- Included documentation: 3D-drawing, technical drawing with dimensions

B Missing outcomes

Table 7 decomposes the difference between the estimation sample of 16,487 graduates and the outcome-specific samples. Attrition is driven primarily by the 2023 cohort, for which Year-1 outcomes are not yet observed, and, for earnings, by the restriction to individuals employed throughout the full calendar year (see Section 2).

Table 7: Missing outcomes

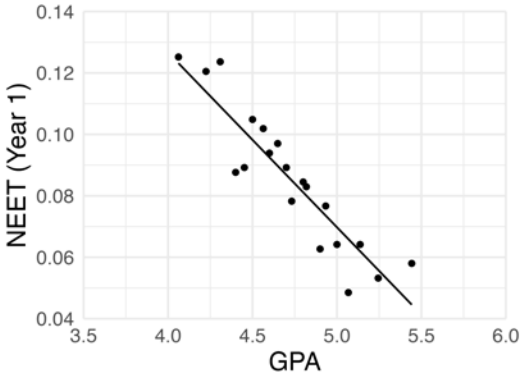
Outcome / reason	N
NEET (Year 1)	3710
... Year 1 not observed (cohort of 2023)	3056
... still in upper secondary education	390
... in military service	264
Earnings (Year 1)	5973
... Year 1 not observed (cohort of 2023)	3056
... below 1^{st} / above 99^{th} percentile dropped	145
... individual was not employed during the whole year	2772
Tertiary (Year 1)	3446
... Year 1 not observed (cohort of 2023)	3056
... still in upper secondary education	390
Stayer	61
... Employer ID missing	61

Notes: Number of observations without a valid value for each outcome, by reason. Outcomes measured in Year 1 are unavailable for the 2023 cohort, which is not yet observed one year after graduation. Individuals still in upper-secondary education or in military service are excluded from the NEET and tertiary-entry outcomes, as their status is not comparable to that of labor market entrants. For earnings, we additionally drop observations below the 1st and above the 99th percentile, and person-years in which the individual was not employed throughout the entire calendar year (see Section 2). Retention is missing only where the employer identifier is unavailable.

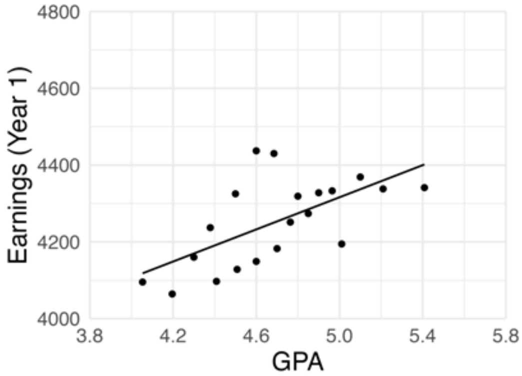
C Additional results and robustness

C.1 Descriptive scatter plots

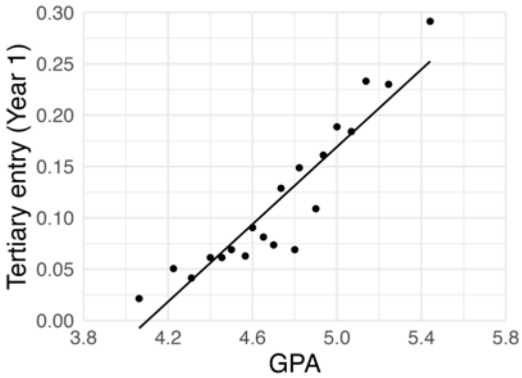
Figure 5: Overall grades and labor market outcomes



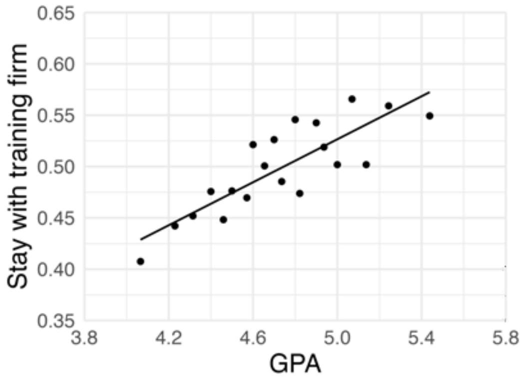
(a) NEET (Year 1) and GPA



(b) Earnings (Year 1) and GPA



(c) Tertiary entry (Year 1) and GPA



(d) Stayer and GPA

Binscatter plots with the outcome variables (a) NEET probability in year 1; (b) Effective earnings during year 1; (c) Probability of entering tertiary level in year 1; (d) Probability of staying with the training firm. The x-Axis variable is the overall GPA. Binscatter plots display the mean of the outcome within bins of the running variable, yielding a denoised relationship. We partition x into 20 quantile-spaced bins with approximately equal counts. N = 16,487.

C.2 Additional results

Table 8: Theoretical and practical grades and different outcomes, standardized grades

	(1)	(2)	(3)	(4)
Panel A: Grades and NEET (Year 1), N= 12,777				
Vocational practice (std)	-0.017***			-0.015***
	(0.003)			(0.003)
Vocational knowledge (std)		-0.011***		-0.004
		(0.003)		(0.003)
General knowledge (std)			-0.011***	-0.005
			(0.003)	(0.004)
Panel B: Grades and earnings (Year 1), N= 10,514				
Vocational practice (std)	84.375***			72.808***
	(9.982)			(10.474)
Vocational knowledge (std)		61.457***		34.059***
		(10.676)		(11.827)
General knowledge (std)			49.887***	17.697
			(11.875)	(13.045)
Panel C: Grades and Tertiary (Year 1), N= 13,041				
Vocational practice (std)	0.031***			0.019***
	(0.003)			(0.003)
Vocational knowledge (std)		0.040***		0.022***
		(0.003)		(0.003)
General knowledge (std)			0.048***	0.034***
			(0.003)	(0.004)
Panel D: Grades and stayer, N= 16,426				
Vocational practice (std)	0.055***			0.051***
	(0.004)			(0.004)
Vocational knowledge (std)		0.026***		0.004
		(0.005)		(0.005)
General knowledge (std)			0.032***	0.017***
			(0.005)	(0.005)
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓

Notes: General knowledge, vocational knowledge, and vocational practice are in a standardized form (std) with mean 0 and a standard deviation 1. Dependent variables: (A) NEET probability in year 1; (B) Effective earnings during year 1; (C) Probability of entering tertiary level in year 1; (D) Probability of staying with the training firm. Sample sizes vary by outcome; see Appendix Table 7. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

C.3 Additional heterogeneity

Table 9: Grades and NEET (Year 1)

	(1) manual	(2) cognitive	(3) routine	(4) non-routine
Vocational practice	-0.031***	-0.030***	-0.070***	-0.025***
	(0.010)	(0.009)	(0.021)	(0.007)
Vocational knowledge	-0.001	-0.025***	0.021	-0.016**
	(0.009)	(0.009)	(0.017)	(0.007)
General knowledge	-0.019*	0.005	0.003	-0.010
	(0.011)	(0.010)	(0.024)	(0.008)
Mean of outcome	0.086	0.072	0.075	0.080
Observations	5809	5361	1259	9911
	(5) female	(6) male	(7) stayer	(8) leaver
Vocational practice	-0.024***	-0.044***	-0.029***	-0.034***
	(0.008)	(0.009)	(0.008)	(0.010)
Vocational knowledge	-0.016*	-0.005	-0.016**	-0.000
	(0.009)	(0.008)	(0.007)	(0.009)
General knowledge	-0.005	-0.009	-0.004	-0.011
	(0.010)	(0.010)	(0.008)	(0.011)
Mean of outcome	0.068	0.099	0.061	0.108
Observations	5705	7072	6236	6508
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓

Notes: Subsample (linear) regressions on the subsamples characterized by the title of the column. Dependent variable: NEET probability in year 1. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Grades and tertiary entry (Year 1)

	(1) manual	(2) cognitive	(3) routine	(4) non-routine
Vocational practice	0.034***	0.059***	0.072***	0.042***
	(0.010)	(0.013)	(0.024)	(0.009)
Vocational knowledge	0.025***	0.077***	0.060***	0.044***
	(0.008)	(0.012)	(0.020)	(0.007)
General knowledge	0.055***	0.083***	0.045**	0.073***
	(0.009)	(0.013)	(0.022)	(0.008)
Mean of outcome	0.082	0.182	0.107	0.133
Observations	5960	5453	1280	10133
	(5) female	(6) male	(7) stayer	(8) leaver
Vocational practice	0.054***	0.037***	0.042***	0.047***
	(0.012)	(0.009)	(0.011)	(0.011)
Vocational knowledge	0.061***	0.022***	0.046***	0.032***
	(0.010)	(0.007)	(0.009)	(0.008)
General knowledge	0.087***	0.044***	0.065***	0.064***
	(0.012)	(0.008)	(0.010)	(0.009)
Mean of outcome	0.167	0.080	0.114	0.122
Observations	5720	7321	6362	6645
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓

Notes: Subsample (linear) regressions on the subsamples characterized by the title of the column. Dependent variable: Probability of entering tertiary level in year 1. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: Grades and stayer

	(1) manual	(2) cognitive	(3) routine	(4) non-routine	(5) female	(6) male
Vocational practice	0.133***	0.115***	0.121***	0.125***	0.111***	0.118***
	(0.015)	(0.015)	(0.033)	(0.011)	(0.015)	(0.014)
Vocational knowledge	0.017	-0.022	0.029	0.001	-0.016	0.023**
	(0.013)	(0.015)	(0.030)	(0.010)	(0.015)	(0.011)
General knowledge	0.041***	0.012	-0.026	0.032***	0.008	0.052***
	(0.015)	(0.016)	(0.033)	(0.012)	(0.016)	(0.013)
All covariates	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Mean of outcome	0.499	0.505	0.546	0.496	0.481	0.512
Observations	7387	6994	1602	12779	7296	9130

Notes: Subsample (linear) regressions on the subsamples characterized by the title of the column. Dependent variable: Probability of staying with the training firm. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

C.4 Regression with 2-dimensional continuous overall performance vs. practical orientation

Table 12: Practical orientation, overall performance, and early outcomes

	(1) NEET (Year 1)	(2) Earnings (Year 1)	(3) Tertiary (Year 1)	(4) Stayer
Practical orientation	-0.023***	104.365***	-0.006	0.084***
	(0.007)	(26.223)	(0.008)	(0.011)
Overall performance	-0.041***	210.402***	0.135***	0.111***
	(0.008)	(27.526)	(0.008)	(0.011)
Practical o. × overall p.	0.002	-3.582	0.003	0.005
	(0.003)	(10.117)	(0.003)	(0.004)
Intercept	0.036	3392.414***	0.268***	0.292
	(0.073)	(267.823)	(0.075)	(0.207)
All covariates	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Mean of outcome	0.085	4252.746	0.118	0.498
Observations	12,777	10,514	13,041	16,426

Notes: Dependent variables: (1) NEET probability in year 1; (2) Effective earnings during year 1; (3) Probability of entering tertiary level in year 1; (4) Probability of staying with the training firm. Sample sizes vary by outcome; see Appendix Table 7. Covariates: female; age; migration background; lower-secondary school track; urbanity of residence; dummies for prior upper-secondary degree, failed exam (first attempt), contract termination, bridge-year program, and VET as first choice; fixed effects for occupation and cohort. Robust standard errors in parentheses. FE-variables included as binary indicators. * p<0.10, ** p<0.05, *** p<0.01.

D Predictive value of practical skills

D.1 Improving prediction accuracy by including grade variables

To quantify the predictive value of different information sets, we implement a repeated out-of-sample prediction exercise. For each outcome, we compare six nested predictor sets: (i) a naive benchmark that predicts the outcome by the training-sample mean only, (ii) a baseline specification using standard background characteristics, (iii)-(vi) baseline plus general knowledge, vocational practice, vocational knowledge, or GPA. Categorical predictors are treated as factors and are therefore entered flexibly through a full set of indicator variables.

Prediction performance is evaluated using repeated 5-fold cross-validation. In each repetition, the sample is randomly partitioned into 5 folds: one fold is held out as a test set, while the model is estimated on the remaining folds. This is repeated until each fold has served once as the test set. For binary outcomes, folds are stratified by the outcome to preserve class proportions across training and test samples. This procedure yields genuinely out-of-sample predictions for each observation and avoids evaluating models on the same data used for estimation.

Our prediction model is the LASSO. Operationally, all predictors are translated into a common design matrix, with categorical variables represented by dummy-variable expansions. The LASSO penalty parameter is selected within the training sample by internal cross-validation only. Hence, no information from the held-out test fold is used during model tuning. This is important because the goal is not in-sample fit, but the incremental out-of-sample predictive content of the additional skill variables.

We report two prediction metrics. First, we use the mean absolute error (MAE),

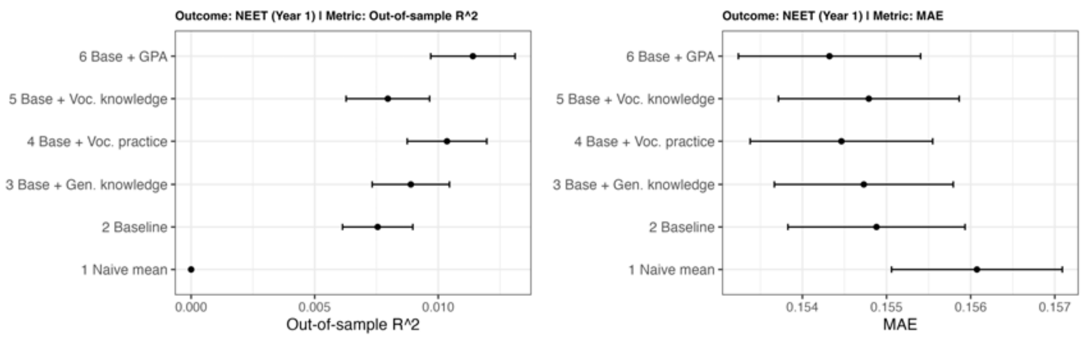
$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| ,$$

which measures the average absolute prediction error and is easy to interpret in the units of the outcome. Second, we report the out-of-sample R^2, defined fold-by-fold relative to the naive mean benchmark as

$$R^2_{\text{oos}} = 1 - \frac{\text{MSE}_{\text{model}}}{\text{MSE}_{\text{naive}}},$$

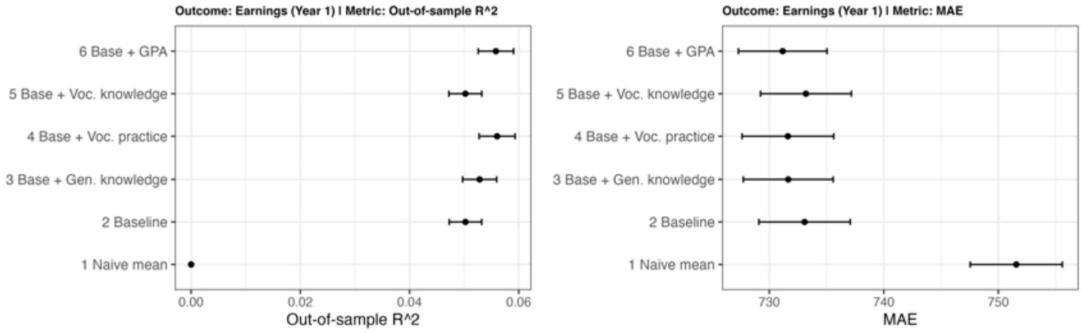
where $\text{MSE}_{\text{model}}$ is the mean squared prediction error of the respective model on the test fold and $\text{MSE}_{\text{naive}}$ is the corresponding mean squared error from predicting the training-sample mean. Under this definition, a value of zero indicates no improvement over the naive benchmark, positive values indicate better predictive performance, and negative values indicate worse predictive performance. We summarize the resulting distribution of fold-level performance measures across repetitions for each outcome-predictor set.

Figure 6: NEET in year 1



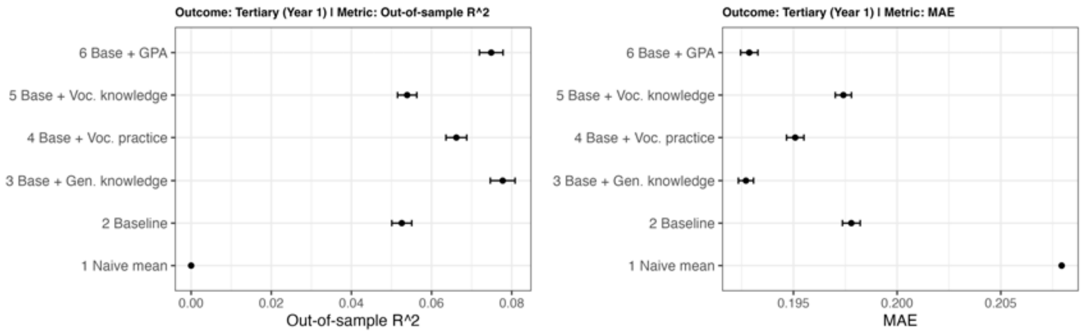
The left graph uses out-of-sample R^2, the right graph uses the mean absolute prediction error (MAE) as evaluation metric. The method used is a LASSO.

Figure 7: Earnings in year 1



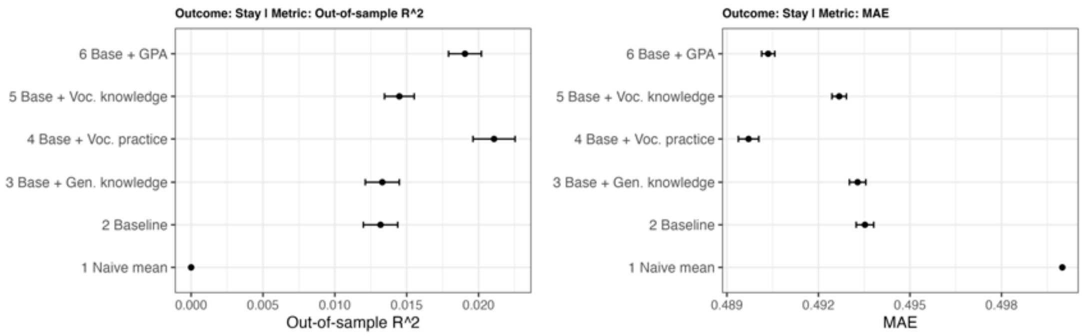
The left graph uses out-of-sample R^2, the right graph uses the mean absolute prediction error (MAE) as evaluation metric. The method used is a LASSO.

Figure 8: Tertiary entry in year 1



The left graph uses out-of-sample R^2, the right graph uses the mean absolute prediction error (MAE) as evaluation metric. The method used is a LASSO.

Figure 9: Stay with training firm



The left graph uses out-of-sample R^2, the right graph uses the mean absolute prediction error (MAE) as evaluation metric. The method used is a LASSO.

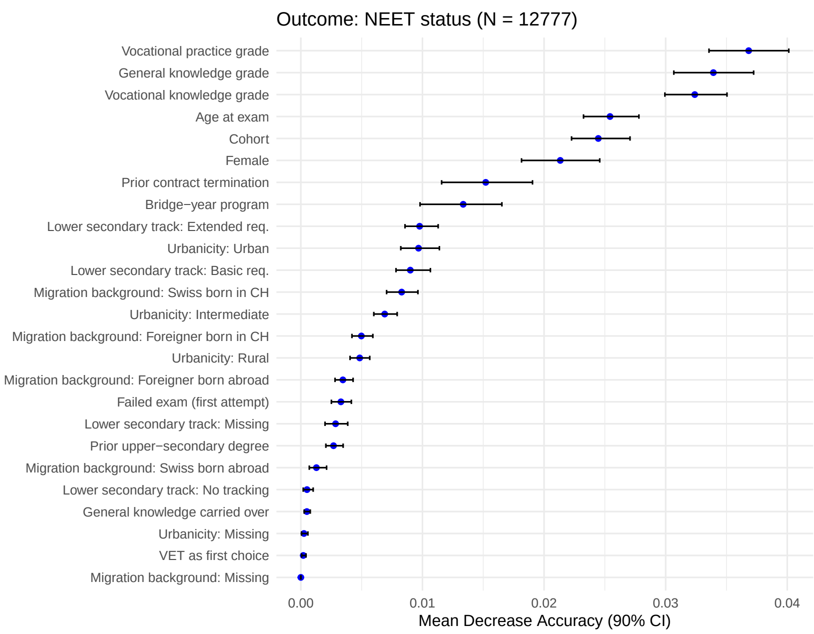
D.2 Variable importance

In this section, random forest (RF) permutation variable importance is conducted to rank predictors by how much they improve out-of-bag predictive accuracy, i.e., to identify which variables are most useful for prediction (not causation). Concretely, we draw B bootstrap samples, fit an RF to each, compute permutation importance (Mean Decrease in Accuracy, MDA) for every predictor, and summarize the per-variable distribution across bootstraps.

Reported below are the bootstrap means and percentile confidence intervals, which quantify the sampling variability of importance. Missing data are handled as follows: for numeric predictors, we add a missingness indicator and mean-impute the original variable; for categorical predictors, we add an explicit "NA" category and then create binary indicator variables for each category (including the NA category), so that the model can learn patterns linked to missingness.

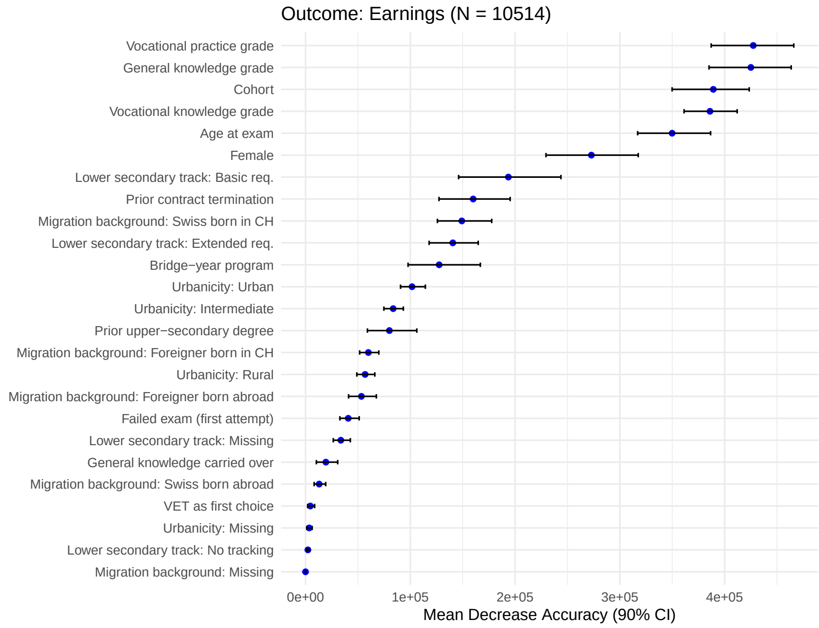
An MDA of 0.05 means that permuting this variable raises the mean squared prediction error by 5 percentage points, reflecting predictive contribution conditional on the other variables. To compare variables, rank them by MDA and consult CIs: larger MDAs with non-overlapping intervals indicate more reliable contributions. MDA values depend on the fitted model and preprocessing and should not be read as causal effects.

Figure 10: Variable importance for first-year NEET status



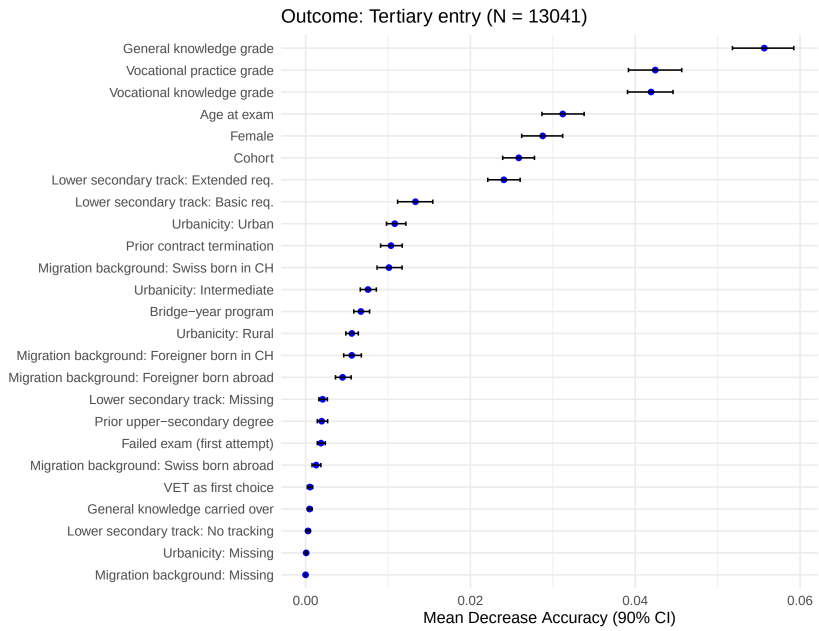
The figure reports random-forest permutation variable importance based on 299 bootstrap samples. Points show the average mean decrease in accuracy across bootstrap samples; horizontal bars show 90% percentile intervals. Higher values indicate that permuting the respective variable increases prediction error more strongly, implying greater predictive relevance conditional on the other variables in the model.

Figure 11: Variable importance for first-year earnings



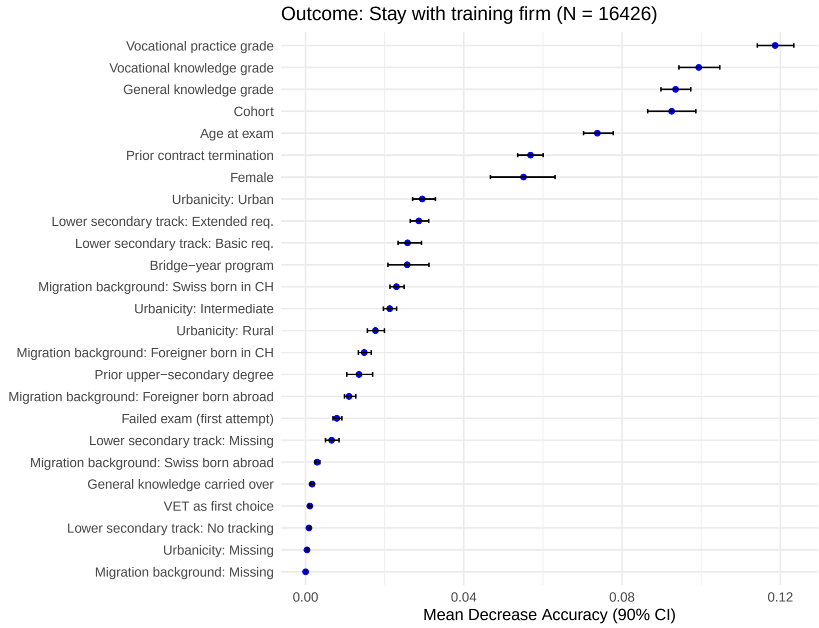
The figure reports random-forest permutation variable importance based on 299 bootstrap samples. Points show the average mean decrease in accuracy across bootstrap samples; horizontal bars show 90% percentile intervals. Higher values indicate that permuting the respective variable increases prediction error more strongly, implying greater predictive relevance conditional on the other variables in the model.

Figure 12: Variable importance for tertiary entry in year 1



The figure reports random-forest permutation variable importance based on 299 bootstrap samples. Points show the average mean decrease in accuracy across bootstrap samples; horizontal bars show 90% percentile intervals. Higher values indicate that permuting the respective variable increases prediction error more strongly, implying greater predictive relevance conditional on the other variables in the model.

Figure 13: Variable importance for staying with the training firm



The figure reports random-forest permutation variable importance based on 299 bootstrap samples. Points show the average mean decrease in accuracy across bootstrap samples; horizontal bars show 90% percentile intervals. Higher values indicate that permuting the respective variable increases prediction error more strongly, implying greater predictive relevance conditional on the other variables in the model.