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# Skills and Earnings: A Multidimensional Perspective on Human Capital

## Abstract

The multitude of tasks performed in the labor market requires skills in many dimensions. Traditionally, human capital has been proxied primarily by educational attainment. However, an expanding body of literature highlights the importance of various skill dimensions for success in the labor market. This paper examines the returns to cognitive, personality, and social skills as three important dimensions of basic skills. Recent advances in text analysis of online job postings and professional networking platforms offer novel methods for assessing a wider range of applied skill dimensions and their labor market relevance. A synthesis and integration of the evidence on the relationship between multidimensional skills and earnings, including the matching of skill supply and demand, will enhance our understanding of the role of human capital in the labor market.

JEL-Codes: J240, I260.

Keywords: skills, human capital, education, labor market, earnings, tasks, cognitive skills, personality, social skills, multidimensional skills.

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# 1. Introduction

The study of the supply and demand for human capital is a core part of attempts in labor economics to understand the evolution and distribution of earnings. When analyzing how technological change affects the earnings structure, the interaction between worker skills and emerging job tasks is central to what has become the workhorse model, the task framework (e.g., Acemoglu and Autor (2011); Autor (2022)). Despite the obvious multitude of tasks performed in the labor market, empirical measurement of skills often remains unidimensional, relying on educational attainment as a proxy. However, educational attainment measures an input rather than the outcome of the skill formation process, failing to capture the full multidimensionality of workers' skills. Scattered literatures demonstrate that various dimensions of skills – both cognitive and noncognitive – are strongly associated with earnings. This review synthesizes these diverse strands of literature which inform about the relationship between different types of skills and earnings and discusses how a perspective of multidimensional skills can enhance our understanding of earnings variation in the labor market.

Classical human capital models posit that individuals invest in their skills to enhance their productivity, thereby earning higher wages (Section 2). Conceptually, different vintages of labor models increasingly highlight the multitude of skills required for various job tasks. Despite these theoretical advancements, empirical measurement has not fully embraced the multidimensional perspective. We consider skills as workers' capabilities to perform productive tasks. In this sense, components of personality traits and preferences that capture capabilities valuable in production reflect skills. We propose a distinction between basic and applied skills: applied skills are directly employed in executing tasks, whereas basic skills serve as the foundation to acquire applied skills and facilitate task performance. We classify the basic skills covered in the literature into three categories: cognitive, personality, and social skills.

A substantial body of literature consistently demonstrates strong associations between cognitive skills and earnings (Section 3). Longitudinal studies tracking adolescents into the labor market and cross-sectional studies assessing workers' skills show comparable results for early-career earnings. Associations are even stronger in workers' prime working years, reflecting lifetime earnings. Earnings associations have been documented for math skills (numeracy) and verbal skills (literacy). In the United States, returns to cognitive skills increased in the late 20$^{th}$ century and decreased moderately in the early 21$^{st}$ century. But the decrease is an international exception, and U.S. returns remain notably high compared to other countries. Estimates of cognitive skill returns are large enough to account for most of the returns to years of education.

Earnings are also associated with various noncognitive skills. However, as a defining term, “noncognitive” is vague and imprecise, impeding understanding. Furthermore, virtually all skills classified as noncognitive have a cognitive component; for instance, leadership, teamwork, and attribution of locus of control all entail cognitive processes. Therefore, we distinguish two main areas within the noncognitive literature: personality traits and social skills.

Certain personality traits exhibit consistent evidence of labor market returns (Section 4). Notably, conscientiousness and internal locus of control are frequently associated with higher earnings. Interpreted as skills, these traits may enhance workers’ capability to perform work tasks with greater effectiveness and persistence. In contrast, evidence linking other personality traits to labor market returns is less robust.

Given that most production processes involve interpersonal interactions, social skills can play a crucial role in facilitating the performance of individual and collaborative work tasks (Section 5). In vertical interactions, leadership skills – and potentially obedience – can enhance the effectiveness of performing tasks. Teamwork skills and sociability are important for horizontal interactions among peers. Empirical analyses using various proxies reveal positive returns to leadership and teamwork skills. Social skills appear increasingly complementary to cognitive skills, and their returns tend to trend upwards in recent decades.

The allocation of several skill dimensions across different work tasks makes the significance of skill multidimensionality particularly evident (Section 6). Recent contributions to labor market search and occupational choice derive measures of skills in cognitive, social, and technical domains. Results indicate that mismatch between the skills supplied by workers and those demanded by employers can significantly impact earnings.

Big data applications of online job postings and professional networking platforms have advanced the measurement of multidimensional skills (Section 7). These methods reveal a diverse range of applied skills demanded by firms and supplied by workers, highlighting the complexity of a broad spectrum of skill dimensions in earnings determination.

Overall, this review demonstrates that there is a multitude of skills that pay off in the labor market. To fully comprehend the role of human capital in earnings generation, it is essential to integrate and synthesize these various skill dimensions, assess their individual and interactive relevance, and explore their evolution with technological changes in the economy. Advances in data collection and measurement techniques offer substantial opportunities to enhance the analysis of various skill dimensions. These developments provide real scope for expanding and refining our understanding of how multidimensional skills influence labor market outcomes.

## 2. Conceptual Background

To provide a framework for the review, we discuss the role of skills in different labor models (Section 2.1), introduce a framework to think about different types of skills (Section 2.2), and discuss conceptual aspects of the empirical model that links skills to earnings (Section 2.3).

### 2.1 Developments in Human Capital Theory and Measurement

**Classical human capital theory.** The idea that skills raise productivity and outcomes in the labor market is the very basis of modern human capital theory. People spend time, money, and effort to acquire useful skills and knowledge that have economic value when used in production, so that substantial parts of their productive capacity are the outcome of deliberate investment in human capital (Schultz (1961)).

In the absence of any direct measure of skills, the empirical literature has initially reverted to testing the human capital model by estimating earnings returns to higher levels of educational attainment (Becker (1964); Mincer (1974)) – and it has mostly continued to do so ever since (e.g., Griliches (1977); Card (1999); Heckman, Lochner, and Todd (2006)). To make the empirical analysis tractable, the study of returns to skills has mostly been reduced to returns to education or, more explicitly, returns to years of school attainment.

**The education-technology race model.** When applying the basic human capital concept to study the earnings distribution, the canonical model studies the supply and demand for skills. In a setting of two differently skilled worker groups that produce two types of goods, the return to skills depends on their scarcity that emerges from a race between production technologies that demand higher skills and the supply of these skills as acquired in college (Tinbergen (1974); Goldin and Katz (2008)). Ever since the seminal contribution by Katz and Murphy (1992), empirical tests of the model again revert to measured educational attainment, usually an indicator for college degrees (e.g., Autor (2014); Autor, Goldin, and Katz (2020)).

**The task framework.** The key innovation of the task framework, which has become the workhorse model to study the earnings structure, is to consider that the performing jobs involves accomplishing a broad range of tasks. Performing specific tasks requires certain skills, and new production technologies can take over task performance from workers (Acemoglu and Autor (2011)).[1] Depending on the respective returns, workers allocate their skills to the performance of different tasks such as routine, non-routine manual, and abstract tasks. But although worker skills motivate the entire task-based approach to how labor markets adjust to technological change, the consideration of multidimensional tasks has not been matched by multidimensional measurement of skills on the empirical side. While the tasks required in different jobs are richly described, worker skills are still mostly proxied rudimentarily by educational degrees (e.g., Autor, Levy, and Murnane (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2022)).

**Multidimensional skills.** Despite the focus on educational attainment in the empirical labor literature, the idea of human capital theory is about skills, and the skill vector relevant in the labor market likely has many dimensions. Particularly in a framework of multiple tasks, it would be natural to consider not only skills that are generally employable, but particularly skills that are specific to certain tasks (Gathmann and Schönberg (2010); Sanders and Taber (2012)). In the spirit of the described models, the value of various skills depends on the production technology employed (which determines the demand for different skills) and on their respective supply in the workforce. Bringing the labor market into equilibrium, the return to any given skill reflects the scarcity of its supply relative to its demand. Returns thus depend on context. If trends in returns differ for different degrees and skills, fully understanding the earnings structure in a given context requires consideration of more than one skill dimension (Deming (2023)). Thus, the important empirical innovation of the standard Mincer (1974) formulation that depicts human capital by educational attainment in earnings analyses was maybe too successful as it led to an ignorance of the multidimensionality of skills and their sources, an aspect required to capture the full relevance of skills for earnings (Hanushek et al. (2015); Hanushek et al. (2022)).

### 2.2 A Framework of Different Dimensions of Skills

The basic concept of skills refers to capabilities that workers need to perform work tasks that contribute to production (e.g., Bowles, Gintis, and Osborne (2001a); Acemoglu and Autor (2012)). By making workers more productive – performing a task in a faster or better way or

[1] One implication of the framework is that technological change can lead to polarization in the labor market (e.g., Autor and Dorn (2013)). Recent studies extend the analysis to consider the evolution of tasks but retain the basic task setup (e.g., Acemoglu and Restrepo (2018); Autor et al. (2024)).

expanding the set of performable tasks – skills allow them to earn more in the labor market. Human capital theory emphasizes the investment character of skill accumulation: in most cases, skills can be learned by investing time and effort in schools, in families, at work, in training courses, through practice, or in any other way. But some productive skills may also partly or entirely be innate, inherited, or possessed by chance.

**Skill classification.** Conceptually, we suggest dividing skills into two types (which span a continuum rather than constituting a dichotomy): basic and applied. Basic skills are usually not directly used to perform work tasks but are mostly used as inputs to learn other, more applied skills. Applied skills, by contrast, are mostly used to perform work tasks directly.[2] For example, school-level math or science skills are mostly not directly used in performing a production task, but they are the foundation to acquire other skills. Teamwork skills or conscientiousness are also mostly not directly needed to perform a work task, but they mediate how effectively various applied skills are used to perform particular tasks. Examples of applied skills that build on basic skills (and whose usage is often mediated by them) include using or programming computer software (such as Microsoft Office, Java, or AutoCAD), financial analysis, marketing, graphic design, customer relations, or biotechnology.

**Basic skills.** We distinguish three broad categories of basic skills studied in the literature: cognitive, personality, and social skills. Skills in various cognitive domains such as verbal, math, and science skills provide the cognitive foundation for learning more applied skills. Cognitive skills thus underly many of the more directly productive skills that allow workers to perform certain tasks. Personality traits such as conscientiousness or locus of control can be viewed as skills that affect the effectiveness or persistence with which individual workers perform their tasks. Social skills can facilitate interpersonal interaction within firms and with customers. In a world with wide division of labor among workers with different skills, production processes can be facilitated, and outcomes improved, if workers are able to work effectively in groups.

**Applied skills.** While it may be possible to classify basic skills into a limited number of meaningful categories, the full multidimensionality of skills becomes apparent when turning to applied skills required directly to perform various concrete job tasks. Many applied skills have a strong cognitive component (e.g., applying computer software, insurance) and others have a

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[2] Note that this distinction is not the same as the one between general and specific skills, where specificity usually refers to applicability within a certain occupation, industry, or firm (see below).

strong social component (e.g., customer relations, communication), thus building on basic skills. Applied skills can also include technical or manual components.

Many applied skills are specific to an industry (e.g., banking, healthcare, hospitality) or occupation (e.g., marketing, architecture, recruiting), but others are more generally applicable (e.g., product design, management, foreign languages). Thus, the distinction between basic and applied skills is conceptually different from the distinction between general and specific skills, which refers to usability across or within industries, occupations, firms, or even tasks.[3]

**Skills, personality traits, and preferences.** The concept of skills is related to other concepts such as personality traits and economic preferences. In fact, there is no sharp delineation between these concepts. To the extent that personality and preferences include capabilities that are valuable in production, these components reflect skills. Personality traits such as consciousness and locus of control are relevant for success in the labor market, thus constituting skills in the sense of the term used here; Borghans et al. (2008) employ the term "personality skill" (see also Almlund et al. (2011)). Apart from time and risk preferences, several standard dimensions of economic preferences such as reciprocity, altruism, and trust (e.g., Falk et al. (2018)) are social preferences and as such closely related to social skills. Personality traits and sociability are categories that may entail a certain amount of innateness or predisposition. However, both have been shown to be malleable (e.g., Borghans et al. (2008); Almlund et al. (2011); Kosse et al. (2020)), they can be learned and accumulated to some extent – and, as we will see, they have payoffs in the labor market. As such, there are parts of personality traits and preferences that should be considered as skills.

### 2.3 General Conceptual Considerations on Empirical Models and Measurement

**Empirical model.** To depict the relationship between skills and earnings in an empirical model, most studies follow the Mincer (1974) specification of expressing log earnings as a function of human capital measures:

$$\ln Y_i = \beta_0 + \beta_1 S_i + \beta_2 C_i + \varepsilon_i \qquad (1)$$

[3] The aspect of general versus specific skills, a key component of the initial work by Becker (1964), is capably covered in Sanders and Taber (2012).

where $Y$ are earnings of individual $i$, $S$ is a multidimensional vector of skills, $C$ is a vector of control variables, and $\varepsilon$ is an idiosyncratic error term. As such, the estimated coefficient $\beta_1$ reflects the percent increase in earnings for a one unit increase in skills.

In most applications, skill measures are standardized, so that a unit reflects one standard deviation in the respective skill measures. This standardization is convenient, as it allows for a direct comparison of coefficients across very different skill measures that often do not have a natural scale or interpretation.

However, there are limits to interpreting different standardized estimates as comparable. Consider two populations where one has twice the variation in a skill than the other and where the skill has the same effect in both populations. As a result, the outcome will also have twice the variation in the former population. Standardizing the skill measure (but not the outcome) – i.e., setting a unit equal to one standard deviation in the respective population – implies that the coefficient estimate would be twice as large in the former compared to the latter population, even though the true effect is the same in both populations. In that sense, comparability is only given for populations (over space, time, or other characteristics) that exhibit roughly the same variation in the underlying skill. Similarly, different skills may have very different variation in a given population, limiting comparable interpretability of standardized coefficients on different skills even when estimated within the same population.

In our analysis, we are genuinely interested in how workers' skills relate to their earnings. Skills reflect workers' human capital. We do not use skills (only) as a proxy for what is learned in school. Nor do we think that years of education or degrees are encompassing proxies for skills. Skills can stem from many sources including innate factors $I$, fostering and learning in families and social environments $F$, formal educational institutions $E$, and learning on the job $J$:

$$S_i = f(I_i, F_i, E_i, J_i) \tag{2}$$

In this framework, it is obvious that the control vector $C$ in equation (1) should not include measures of educational attainment, as these are part of the source vector $E$ of skills. As such, they would be bad controls in estimating the full skill-earnings association. Not least because of other skill sources, they would also be insufficient measures of the full set of workers' skills.

Similarly, measures of intelligence will proxy only insufficiently for relevant skills. Traditionally, intelligence or IQ have been interpreted as part of the innate sources $I$ of skills.

While common measures of intelligence have been shown to be malleable by schooling and educational interventions (e.g., Heckman (1995)), they are meant to capture a component that is less malleable than broader measures of academic achievement. Thus, IQ measures will miss important sources of skills, particularly those that develop over a person's life.[4]

**Measurement error and objectivity in skill measurement.** More generally, the multidimensionality of skills and their emergence from various sources highlight the importance of measurement and the point that skill concepts can be measured with varying measurement error. For example, on the cognitive side, a wide range of measures of varying breadth has been used to measure cognitive skills, ranging from ultra-short IQ tests (e.g., Heineck and Anger (2010)) and other tests such as the Armed Forces Qualifying Test (AFQT, e.g., Neal and Johnson (1996); Altonji and Pierret (2001); Deming (2017)) that are often interpreted as IQ measures to hour-long tests of verbal and numerical skill dimensions such as the Programme for the International Assessment of Adult Competencies (PIAAC, e.g., Hanushek et al. (2015)). Estimates of skill returns based on short measures of cognitive ability will tend to suffer from greater attenuation bias than broader test measures of overall achievement.

Similarly, on the noncognitive side, measurement ranges from indicators such as club participation in high school (e.g., Deming (2017)) to more encompassing psychological assessments such as the Rosenberg (1965) Self-Esteem Scale, the Rotter (1966) Locus of Control Scale, and item batteries of various lengths to measure the so-called Big Five psychological traits. For instance, the original extensive 60-item version of the Rotter scale has also been used in a four-item abbreviated version (e.g., Heckman, Stixrud, and Urzua (2006)). Where available, reliability ratios can be used to scale estimates up for the amount of measurement error with which a skill concept is measured (e.g., Edin et al. (2022)), but the wider topic is the breadth of the concept that is being measured. The quality and richness of measurement affect the interpretation of estimated associations of skill measures with earnings.

Relatedly, there is a continuum of measurement from subjective to objective measures. Cognitive skills are often measured by tests of achievement, where participants cannot fake higher achievement. At the same time, tested achievement can depend on test motivation and effort, which can be influenced by the stakes attached to the test. Achievement testing is harder

[4] An older literature used IQ measures to purge estimates of returns to schooling from ability bias and as such contains estimates of returns to IQ measures conditional on years of education (see Griliches (1977)).

for many noncognitive domains, so that measurement often reverts to self-assessments in surveys. Subjective assessments may depend on behavioral traits in answering behavior, and their truthfulness is hard to assess. An alternative are assessments by experts on prespecified scales, whose objectivity may lie between subjective self-assessments and achievement tests.

**Timing of measurement of earnings and skills.** To study the full bearing of skills on earnings, we would like to observe the set of skills that workers possess when working in the job that generates their earnings. This is the case in adult skill surveys that measure workers' skills together with observing their current earnings. By contrast, many studies are primarily interested in how skills obtained in school relate to subsequent earnings. This is possible in longitudinal studies that observe students' skills and follow them into the labor market, which also shields against bias from any reverse causation from earnings to subjective skill reporting. However, this approach misses any development in skills between school and work outcomes.

While we would ideally be interested in workers' lifetime earnings, earnings are observed at different points in workers' lifecycles. Longitudinal studies that follow students tend to measure earnings early in the career, whereas adult skill studies tend to measure earnings for workers across the entire career. For several reasons, earnings-skills associations are likely to rise over workers' lifecycle. First, employers may not fully observe workers' skills at job entry, so that employer learning will lead to increasing returns to skills (Altonji and Pierret (2001)). Second, matches of skills to jobs may initially be imperfect and improve over the career (Jovanovic (1979)). Third, people with higher lifetime earnings tend to have steeper earnings trajectories during their early careers (Haider and Solon (2006)). Haider and Solon (2006) and Böhlmark and Lindquist (2006) show that earnings observed in prime age (roughly between mid-30s and late-40s) are a good proxy for lifetime earnings. By contrast, estimates of the association of skills with early-career earnings will understate their full association with lifetime earnings.

**Identification.** The available evidence tends to depict (conditional) associations between earnings and skills. Most studies stop short of aiming to identify exogenous variation in skills, which would be required to interpret the associations as causal effects of skills. Apart from attenuation biases due to measurement error, there are two main sources of potential bias. First, higher-paying jobs may reinforce skills, and lower-paying jobs may lead to a loss of skills due to a lack of practice. This reverse causation can give rise to an association between skills and earnings that does not reflect a causal effect of skills in studies using adult skill surveys (but not in longitudinal studies that observe skills before labor market entry). Second, other factors such as family background or health may be correlated both with skills and earnings. For instance, higher-educated and well-connected parents may foster their children's skills and also help them access higher-paying jobs in other ways. Relatedly, individuals with certain skills may select into jobs with higher earnings. Any association of earnings and skills may thus suffer from omitted-variable bias. Various attempts to identify causal effects based on field experiments (e.g., Chetty et al. (2011)), resume experiments (e.g., Piopiunik et al. (2020)), or natural experiments (e.g., Hanushek et al. (2015)) will be discussed in the respective sections below.

## 3. Cognitive Skills

The skill dimension whose earnings returns have been studied most extensively is cognitive skills. Two approaches employ different specialized data sets that provide the required linkage of skills to earnings: longitudinal data (Section 3.1) and adult skill surveys (Section 3.2). Results consistently show strong earnings premia for skills in several cognitive dimensions.

### 3.1 Longitudinal Studies on Adolescent Skills and Later Earnings

Studies using representative U.S. panel data link cognitive skills from high school to later labor market outcomes. For example, Neal and Johnson (1996) use the National Longitudinal Survey of Youth (NLSY79) to show that higher scores on an approximated AFQT test (measuring paragraph comprehension, word knowledge, arithmetic reasoning, and math knowledge) at ages 15-18 are associated with 22.8 (17.2) percent higher wages at ages 26-29 for women (men) per standard deviation (SD) in cognitive skills. The estimates decrease by over a quarter when controlling for years of schooling, indicating substantial underestimation of the full skill association. Similarly using NLSY79, Mulligan (1999) finds 10.9 percent higher earnings for standardized AFQT scores in models that control more richly for parental income and school quality. Bowles, Gintis, and Osborne (2001a) survey 24 studies such as Bishop (1989) and Murnane, Willett, and Levy (1995) and find a median estimate of 8 percent higher earnings per SD in cognitive skills in models that condition on years of schooling, among others.

In the National Longitudinal Survey of the High School Class of 1972 (NLS72) and High School and Beyond (HSB), Murnane et al. (2000) estimate returns of 6.7-9.5 (11.1-14.7) percent per SD in math skills for women (men) at ages 27-31. Again, estimates decrease strongly (by 47-85 (35-40) percent for women (men)) when controlling for educational degrees. Math skills are highly correlated with reading skills (at 0.65-0.70), suggesting that math coefficients may partly capture reading. Reading skills are less strongly correlated with earnings, and math is the stronger predictor when both are included. Using the National Education Longitudinal Study of 1988 (NELS88), Lazear (2003) finds earnings at age 25 increase by 15.8 percent for a SD in eighth-grade scores (combining reading, math, history, and science) and, in the same model, by 12.5 percent for a SD increase in scores from eighth to twelfth grade.[5]

Longitudinal studies observe earnings early in workers' careers, which may underestimate lifetime returns (see Section 2.3). Indeed, studying men in the NLSY79, Altonji and Pierret (2001) find that AFQT is hardly associated with wages at labor market entry whereas after ten years of experience, wages are 10.5 percent higher for each SD in AFQT. In the same model (identified within two-digit occupations), there are substantial wage returns to years of schooling at entry that decline strongly with experience. The authors interpret these patterns as evidence for employer learning: because of limited information about workers' productivity at entry, firms initially reward easily observed characteristics such as years of schooling. But as they learn about workers' productivity over time, firms increasingly reward true productivity, which is apparently correlated with AFQT scores (which are unknown to employers).[6]

A late-1980s field experiment in Tennessee, Project STAR, randomly assigned children in grades K-3 to differently sized classrooms. Chetty et al. (2011) link math and reading tests to earnings at age 25-27 in administrative tax returns. They find that a one SD increase in cognitive skills measured in kindergarten is associated with 18 percent higher earnings 20 years later, conditional on student and parent socio-demographics. The setup allows for causal identification of early educational quality in the following sense: children randomly assigned to K-3 classroom environments that led to higher test scores have significantly higher earnings at age 27.[7] While not providing random variation in individual skills, the evidence shows that classroom environments that raise early cognitive (but also noncognitive) skills also raise adult earnings.

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[5] Several studies of noncognitive skills, discussed in detail in Sections 4 and 5, also show significant earnings premia to cognitive skills (e.g., Kuhn and Weinberger (2005); Mueller and Plug (2006); Heckman, Stixrud, and Urzua (2006); Lindqvist and Vestman (2011); Weinberger (2014); Gensowski (2018)).

[6] See section 3 of Hanushek and Woessmann (2008) for additional discussion of this literature, including estimates from developing countries.

[7] The classroom environments combine better peers, teachers, and other characteristics. The effect of class size on earnings is small and insignificant (but imprecisely estimated).

Evidence suggests that U.S. returns to cognitive skills first increased and then decreased from the late 1970s to the 2000s. Using a math test commonly scaled in NLS72 and HSB, Murnane, Willett, and Levy (1995) find that returns doubled for females and tripling for males between 1978 and 1986. Similarly, Weinberger (2014) finds a doubling of earnings premia for math scores between 1979 (NLS72) and 1999 (NELS88). Using AFQT scores in NLSY79 and NLSY97, Castex and Dechter (2014) find that returns declined by 30-50 percent for females and males between 1980-1991 and 1999-2008.[8] Similarly, Deming (2017) finds that initially strong returns to AFQT scores of 20.6 percent per SD declined moderately by a quarter in the 2000s.

Results on trends in returns to cognitive skills in Europe are more mixed. Using military conscript data, Edin et al. (2022) find that returns to cognitive skills were relatively stable at 11-13 percent per SD in Sweden between 1992 and 2013. Distinguishing two separate cognitive dimensions in the Swedish conscript data, Hermo et al. (2022) find that the relative return to logical reasoning skills increased compared to vocabulary knowledge. In Finnish conscript data, Izadi and Tuhkuri (2024) find a decline in returns to cognitive skills from 18 to 13 percent per SD between 2001 and 2015. In these studies, however, standardization of scores by cohorts implies that interpretation requires assuming constancy of the underlying skill distribution (see Section 2.3).[9] In Germany, Navarini (2023) does not find significant changes in returns to latent cognitive skills between birth cohorts 1987-1995 and 1996-2003.

Evidence from China suggests broadly similar returns to cognitive skills. In the 2014 China Family Panel Studies (CFPS), Hanushek, Wang, and Zhang (2023) find an earnings premium of 17.0 percent per SD in math scores administered at age ten and above. In the Chinese Household Income Project (CHIP), returns to self-reported scores on the college entrance exam (Gaokao) for graduates from academic-track high schools are estimated at 20.7 percent per SD in 2007, 13.7 percent in 2013, and 16.1 percent in 2018, with little change when conditioning on college degrees (despite strong declines in returns to college degrees).

Overall, the longitudinal studies consistently show significant returns to cognitive skills in the United States and other countries. Estimates mostly fall between 10 and 20 percent higher earnings per SD in cognitive skills, depending on age at earnings observation, informational

[8] The decrease is consistent with an employment decline in occupations intensive in cognitive tasks in the 2000s (Beaudry, Green, and Sand (2016)).

[9] Recent work by Hellerstein, Luo, and Urzúa (2024) suggests that the decline in returns to cognitive skills in the United States may indeed be explained by complex changes in the pre-market skill distribution.

content of skill measures, included controls (especially years of education), and period. An advantage of longitudinal studies is that return estimates do not suffer from reverse causation, as skills are observed years before earnings in the labor market. In addition, the longitudinal evidence is informative for schools. However, the early-career observation of earnings likely underestimates lifetime returns. Furthermore, longitudinal studies do not observe the skills that workers actually have when working, which may be higher or lower depending on adult learning and skill depreciation. Still, the estimated returns to early basic cognitive skills likely include their role in facilitating the subsequent acquisition of more applied skills valuable in job tasks.

### 3.2 Adult Skill Surveys

A second approach to estimate returns to cognitive skills draws on skill surveys of adults. Skill measurement in the adult population, most of which emerges from international testing initiatives, allows for direct linkage of observed skills to current labor market outcomes across the full age spectrum of workers.[10] The most recent and encompassing adult skill survey is PIAAC, an international test administered in 2011-2012 by the Organization for Economic Co-operation and Development (OECD). Country participation was expanded from 23 to 32 in a second testing in 2014-2015. The nationally representative samples cover the population aged 16 to 65. The main assessment tests two dimensions of cognitive skills, literacy (verbal skills) and numeracy (math skills). While designed to assess skills relevant for participation in social life and work, these skill measures are at the basic end of the basic-applied continuum, mostly capturing the basis for acquiring applied skills directly applicable in executing job tasks. A third dimension, problem solving in technology-rich environments, was given only to confident computer users and was optional to countries and participants. The tests are relatively extensive, taking 50 minutes to complete on average (OECD (2013)).

The PIAAC evidence suggests that cognitive skill returns are substantially underestimated when considering earnings only early in workers' careers (Hanushek et al. (2015)). In the United States, earnings increase by 22.6 percent per SD in numeracy skills for early-career workers (25-34 years). Broadly consistent with the longitudinal studies, the PIAAC estimate is at the upper end of the range of longitudinal estimates, which may reflect differing skill trajectories between

[10] Some national adult surveys contain short tests of cognitive ability that have been used to estimate earnings returns. For example, Heineck and Anger (2010) use an ultra-short IQ test of symbol correspondence in the German Socio-Economic Panel and find positive returns for males, but not females.

high school and work, as well as richer skill measurement. Estimated returns increase by roughly a quarter to 27.9 percent per SD for prime-aged workers (35-54 years), which more likely capture lifetime earnings (see Section 2.3).

Allowing comparable estimation across countries, the PIAAC results show significant returns to cognitive skills in all participating countries. When pooling the 32 countries, a one SD increase in numeracy skills is related to 20.0 percent higher earnings on average, 30 percent higher than suggested by estimates from early-career earnings (Hanushek et al. (2015, 2017a)). To address measurement error, Hampf, Wiederhold, and Woessmann (2017) exploit multiple plausible values of the latent skill measure provided by PIAAC's scaling, using one plausible value as instrument for another. The pooled estimate increases to 23.2 percent, indicating that conventional estimates suffer from attenuation bias. Estimated returns do not differ significantly by gender. The estimate is substantially lower (by 43 percent) when controlling for years of schooling, suggesting strong underestimation of the full skill-earnings association.

The international average masks considerable differences in returns to cognitive skills. Estimates range from 10.7 percent in Greece to 45.5 percent in Singapore (Hanushek et al. (2015, 2017a)). In eight countries, including all four Nordic countries, returns fall in the 12-15 percent range. In ten countries, returns are 22 percent or higher. U.S. returns are highest among all participating OECD countries (see also Autor (2014) for a discussion of the international pattern). Some of the cross-country variation reflects systematic country differences: skill returns are lower in countries with higher union density, stricter employment protection, and larger public sectors, but they do not vary with countries' level or inequality of skills (Hanushek et al. (2015)). Returns are also systematically higher in countries with faster prior GDP growth, suggesting that returns to cognitive skills may partly reflect value of the capability to adapt to economic change (Hanushek et al. (2017a)).[11]

PIAAC allows estimating returns to different dimensions of cognitive skills (Hanushek et al. (2015)). Numeracy skills are strongly correlated with literacy (0.87) and problem solving (0.73) skills. Not surprisingly, each skill dimension is thus strongly associated with earnings, with

[11] The hypothesis that returns to education partly reflect a value of the ability to deal with disequilibria goes back to Nelson and Phelps (1966), Welch (1970), and Schultz (1975). Izadi and Tuhkuri (2024) argue that increased returns to extraversion may reflect adaptability to changing environments (see Section 5.3). Relatedly, Deming (2021) and Caplin et al. (2024) study the ability to make resource allocation decisions, termed economic decision-making skills. It is an open question whether the capability to decide and adapt in complex environments reflects a skill dimension of its own, specific cognitive or personality skills, or a combination of different basic skills.

larger estimates for numeracy (0.178 percent per SD) and literacy (0.171) than for problem solving (0.143).[12] When the dimensions are jointly included, all estimates remain significant, but numeracy dominates literacy, and both dominate problem solving.[13]

Explorations into causality suggest that the associations may well be a lower bound of the causal effect of skills on earnings. To obtain exogenous variation, Hanushek et al. (2015) exploit changes in compulsory schooling laws that give rise to variation in PIAAC skills across U.S. states and cohorts. Instrumental-variable estimates are substantially larger (although less precisely estimated) than the OLS estimates.[14] Still, convincing identification of exogenous variation in skills – and particularly in specific skill dimensions – remains a challenge.[15]

Prior work using the International Adult Literacy Survey (IALS) shows returns to cognitive skills (prose, document, and quantitative literacy) in 1994-1998 (e.g., Leuven, Oosterbeek, and Ophem (2004); Blau and Kahn (2005)). Estimates in Hanushek and Zhang (2009) range from 4.9 percent per SD in Sweden to 19.3 percent in the US (conditional on years of education).[16] In the joint sample of 8-11 countries, the correlation of estimates from PIAAC and IALS ranges from 0.66-0.74 for the different IALS studies (and exceeds 0.85 when excluding one outlier).[17]

Combining IALS and PIAAC allows to study changes in returns to cognitive skills between the mid-1990s and the early 2010s in several countries. The comparison requires standardization of scores in the respective cross-section and uses a specification that controls for years of education (available for both surveys), warranting further investigation of different model specifications. Still, a simple comparison suggests that returns to cognitive skills have risen

[12] See Falck, Heimisch-Roecker, and Wiederhold (2021) for a deeper investigation of returns to skills in the domain of problem solving in technology-rich environments.

[13] These results are related to findings that field-specific coursework and major choice in high school have earnings returns, in particular in math and STEM-related fields (e.g., Joensen and Nielsen (2009, 2016); Altonji, Blom, and Meghir (2012); Goodman (2019); Dahl, Rooth, and Stenberg (2023)), as well as field of study choice in college (e.g., Altonji, Arcidiacono, and Maurel (2016); Kirkeboen, Leuven, and Mogstad (2016)).

[14] Hanushek et al. (2015) and Hampf, Wiederhold, and Woessmann (2017) also find increased estimates in the international sample when using other instruments observed before labor market entry – years of schooling and parental education – to address reverse causation, but these are unlikely to solve omitted variable bias.

[15] Piopiunik et al. (2020) provide experimental evidence that grade point averages in school and college, considered as cognitive skill signals on resumes, significantly increase applicants' chances to get interview invitations by human resource managers. Extended IT and foreign language skills also have causal impacts.

[16] Consistent with the IALS and PIAAC results, Edin et al. (2022) find that the returns to similar AFQT-type tests are lower in Sweden at 0.11-0.13 percent than in the United States at 0.15-0.20 percent, even though the Swedish estimates refer to prime-aged workers and the U.S. estimates to early-career workers.

[17] See Sections 5.1 and 5.2 in Hanushek and Woessmann (2011) for an overview of additional papers that use the IALS data to study cognitive skills and labor market outcomes in various countries.

slightly on average across the ten countries jointly considered in the different studies, from 6.2-8.1 percent in IALS (Leuven, Oosterbeek, and Ophem (2004); Hanushek and Zhang (2009)) to 9.3 percent in PIAAC (Hanushek et al. (2015)). Germany and Poland show particularly strong increases in estimated returns. By contrast, only the United States shows a substantial decline, from 15.5-19.3 percent to 13.8 percent. These comparisons put the evidence from longitudinal studies (see Section 3.1) in perspective, as the US is an outlier in terms of declining returns to cognitive skills and continues to have the highest returns in this group of countries.[18]

It is tempting to relate estimates of cognitive skill returns to estimates of returns to years of education. As a rule of thumb, students gain roughly between one quarter and one third of a SD in cognitive skills on average during one school year.[19] The U.S. return estimate of 28 percent per SD in PIAAC numeracy skills thus implies that the cognitive skills generally learned during one school year would be related to 7-9 percent higher earnings. This magnitude is very close to the typical return estimate of roughly 10 percent per year of education (e.g., Card (1999)). This comparison comes with a lot of caveats, as annual skill gains are only roughly estimated in school, are even less clear in college, and may be associated with other, noncognitive skills, among others. Still, as a rough indication, estimated returns to cognitive skills are large enough to account for most of the estimated returns to years of education.

Overall, results from adult skill surveys are quite consistent with longitudinal studies for early-career earnings but suggest that these underestimate lifetime returns. In the US and a few other countries, earnings premia at prime age exceed 25 percent per SD in numeracy skills. Similar to the longitudinal studies, results indicate a slight decline in U.S. returns from 1994 to 2012. But this decline is an international exception, and U.S. returns remain the highest among OECD countries. Estimates average 23 percent per SD across the 32 PIAAC participants and range from 11 to 45 percent, with cross-country differences related to market flexibility and speed of economic change. Explorative work suggests that causal returns may be at least as large as the descriptive associations, but establishing causality remains a challenge in the literature.

[18] A second round of PIAAC testing has been conducted in 2022-2023, with results scheduled to be released at the end of 2024. When available, the data should for the first time allow to estimate returns to cognitive skills on a common scale over eleven years for many countries.

[19] See Woessmann (2016). Of course, learning gains per year depend on the productivity of schooling, so that they vary across countries, grades, subjects, and tests. Still, average learning gains per school year in developed countries tend to fall in the range of one quarter to one third of within-country SDs, and somewhat lower in lower-performing school systems (e.g., Avvisati and Givord (2023) and the references therein).

# 4. Personality Traits as Skills

"Personality skills" (Borghans et al. (2008)) are basic skills that can affect how effectively workers perform their tasks. Two personality traits with consistent evidence of labor market payoffs are conscientiousness (Section 4.1) and locus of control (Section 4.2). Evidence for earnings premia of other personality traits is more mixed (Section 4.3). As the existing – particularly psychological – literature has been surveyed extensively in Borghans et al. (2008) and Almlund et al. (2011), the main findings are only briefly summarized and updated here.

## 4.1 Conscientiousness

Conscientiousness is the only Big Five personality trait that is consistently significantly associated with better job performance (Almlund et al. (2011)). Described as "the tendency to be organized, responsible, and hardworking", it includes facets such as order, dutifulness, self-discipline, and achievement striving and is generally measured by self-assessed survey items.

Studies indicate that conscientiousness is associated with labor market outcomes across various performance criteria and occupations (Barrick and Mount (1991); Salgado (1997); Bowles, Gintis, and Osborne (2001a)). More recent work supports these findings (e.g., Becker et al. (2012); Prevoo and ter Weel (2015); Gensowski (2018)), although results are by no means universal and can vary by subgroup or setting (e.g., Nyhus and Pons (2005); Mueller and Plug (2006); Heineck and Anger (2010)). Using Finnish conscript data, Izadi and Tuhkuri (2024) find a stable earnings premium for consciousness between 2001 and 2015.

## 4.2 Locus of Control, Self-Esteem, and Emotional Stability (Lack of Neuroticism)

Locus of control captures whether people assign the determination of life events mostly to their own actions as opposed to external factors such as luck. Self-esteem refers to people's assessment of their own worth. Both concepts are related to emotional stability (opposite of neuroticism), the Big Five factor described as "predictability and consistency in emotional reactions, with absence of rapid mood changes" (Almlund et al. (2011)). Judge et al. (2002) show that there is poor discriminant validity among the three traits, marking the same higher-order concept of a positive and proactive view of oneself in the world.

These traits are again usually measured by subjective assessments of various item batteries. Widely used scales are the Rotter (1966) Locus of Control Scale and the Rosenberg (1965) Self-Esteem Scale. Large-scale datasets tend to use only subscales of the original scales. For example, while the original Rotter (1966) scale includes 60 items, the NSLY79 version is abbreviated to four items (e.g., Heckman, Stixrud, and Urzua (2006)).[20]

Several studies show positive earnings premia for internal locus of control and self-esteem.[21] The general evidence on the association of emotional stability with job performance is rather mixed (Almlund et al. (2011)), with some studies finding positive earnings premia (e.g., Nyhus and Pons (2005); Mueller and Plug (2006); Becker et al. (2012)), but others not (e.g., Heineck and Anger (2010); Gensowski (2018)).

Heckman, Stixrud, and Urzua (2006) use measures of locus of control and self-esteem in the NLSY79 to estimate a latent noncognitive factor. Their structural model addresses measurement error and mutual causality and postulates two latent skill factors. The simulated model suggests similar effects (in terms of factor deciles) of latent cognitive and noncognitive skills on wages at age 30. For both skill dimensions, the estimates are larger than conventional estimates because the attenuation bias is larger than the upward bias from endogeneity and reverse causality.

### 4.3 Other Personality Traits

Evidence on earnings premia for the three other Big Five traits – openness to experience, extraversion, and agreeableness – is mixed at best. Reviews of the early literature do not indicate consistent significant associations with job performance (Almlund et al. (2011)). While some more recent studies of Big Five traits also do not find significant earnings associations for these three traits, others do, but sometimes even of opposite signs.[22] Estimates often differ across specifications, gender, and other subpopulations.[23]

Some papers study combinations of various personality traits. For example, the early study by Jencks (1979) combines measures with maximum predictive power that include study habits, industriousness, and perseverance, but also leadership and executive ability (see Section 5.1). More recently, Lindqvist and Vestman (2011) study a combined measure of noncognitive skills of Swedish conscripts. Rather than self-reported surveys, the measure is based on psychologists'

[20] It is not easy to cleanly delineate various concepts of traits and skills. For example, shyness is sometimes used to describe emotional stability (Almlund et al. (2011)) but also to measure sociability (see Section 5.3).

[21] E.g., Andrisani (1977), Duncan and Morgan (1981), Groves (2005), and Heineck and Anger (2010); see Bowles, Gintis, and Osborne (2001a), Groves (2005), and Lindqvist and Vestman (2011) for overviews.

[22] E.g., Nyhus and Pons (2005), Mueller and Plug (2006), Heineck and Anger (2010), Becker et al. (2012), and Gensowski (2018).

[23] Extraversion is closely related to sociability which we discuss further in Section 5.3.

ratings of a personal interview aimed at assessing the ability to serve in the military service and to function in armed combat. The assessment includes aspects of persistence, emotional stability, and social skills. The measure significantly predicts labor market outcomes, in particular participation and earnings of unskilled workers at the lower end of the distribution.

## 5. Social Skills

As most economic processes involve interpersonal interactions, workers with relevant social skills may perform better in the labor market. In vertical interactions, leadership skills may be relevant for workers at higher hierarchical ranks (Section 5.1), whereas traits related to docility and dependability have been discussed for workers at lower ranks (Section 5.2). In horizontal interactions, teamwork skills may improve team performance and customer interactions (Section 5.3). While treated separately, some social skills discussed here are related to personality traits such as conscientiousness and extraversion discussed in the previous section.

### 5.1 Leadership Skills

Leadership skills, an interpersonal skill related to the management of people, may affect outcomes in vertical interactions. Kuhn and Weinberger (2005) use a behavioral measure of whether people acted as captain of a sports team or president of a club in high school, available in Project TALENT, NLS72, and HSB. They also observe self-assessed measures of leadership skills such as influence, elected offices, or chairing meetings in high school.

These measures of leadership skills have wage premia in the labor market. High-school club presidency or captainship is associated with 4-33 percent higher earnings about ten years after high school for white men, conditional on math scores, parental education, club membership, and high school fixed effects (Kuhn and Weinberger (2005)). Former high-school club presidents are also more likely to work as managers, and the wage premium is particularly strong in managerial occupations, consistent with capturing an ability to lead people. Additional analysis suggests that leadership does not just proxy for other psychological or physical traits.[24]

A couple of papers use social skill measures that combine leadership and teamwork skills. Weinberger (2014) shows that participation in sports activities and nonathletic leadership roles are both positively associated with earnings seven years after high school in NLS72 and

[24] In one large high-tech firm, Hoffman and Tadelis (2021) find that managers with higher ‘people management skills’, measured by subordinates’ survey responses, receive larger salary increases.

NELS88. The association of earnings with an interaction of a combined social-skill measure (sports participation or leadership role) and math achievement increases between 1979 and 1999, suggesting increased cognitive-social complementarity. Interpreting the Swedish psychologist-interviewer measure of draftees' ability to function in military service as a measure of teamwork and leadership skills, Edin et al. (2022) find increasing returns between 1992 and 2013.

### 5.2 Obedience and Dependability

An older literature studies interpersonal skills at the other end of the hierarchy in vertical interactions. The argument usually focuses on specific labor market segments characterized by low status and skills and on specific organizations such as large corporate structures. Early work by Bowles and Gintis (1976) and Edwards (1976) argued that workers socialized to function well and without complaint are more successful in hierarchies of large corporations. Rewards to obedience and docility are consistent with a model where employers value preferences that allow them to induce effort at lower cost (Bowles, Gintis, and Osborne (2001b)).

While results are somewhat mixed (Bowles and Gintis (2002)), early work suggested that worker attributes such as docility, dependability, and persistence are valued in low-status and blue-collar labor markets (Bowles and Gintis (1976); Edwards (1976); see also Bowles, Gintis, and Osborne (2001a); Heckman, Stixrud, and Urzua (2006)). Groves (2005) uses principal component analysis (PCA) to extract two factors, labelled aggression and withdrawal, from a social adjustment battery observed at age eleven in the British National Child Development Study (NCDS). Both factors are negatively associated with wages of white women, which may be interpreted as a reward for docility and subordination. Bowles, Gintis, and Osborne (2001b) find the negative association for both women and men whose background characteristics predict low-status occupations. By contrast, in predicted high-status occupations the association is negative for women, but positive for men.

Interpretation of this evidence is not straightforward, however. On the one hand, these traits could reflect aspects such as subordination, obedience, and docility that are mainly rewarded in exploitative vertical relationships. On the other hand, the empirical analogs generally include other aspects such as consciousness, perseverance, dependability, determination, punctuality, and empathy. These traits may be productive in any vertical relationship including appreciative leadership. They may also be valued by co-workers as aspects that facilitate team performance (see next section).

Relatedly, Navarini (2023) separates a set of noncognitive skills that he terms diligence skills from other social skills that capture interpersonal engagement. He argues that diligence skills measure aspects such as discipline, determination, hard-working, and internalized focus. His measurement system, applied to the Youth Questionnaire of the German Socio-Economic Panel (GSOEP), identifies the two latent factors assuming that 'careful work' loads only on diligence and 'communicative personality' only on social skills. Consistent with reduced demand for routine work, results suggest that returns to diligence skills declined substantially between birth cohorts 1987-1995 and 1996-2003, driven by workers with low cognitive skills.

### 5.3 Teamwork Skills and Sociability

Social skills are also relevant in horizontal interactions, affecting the productivity of teams. These skills may be conceptualized as the "ability to work with others" (Deming (2017)) or the "ability to effectively interact with or handle interactions with people, ranging from communication with to caring for to motivating them" (Borghans, Ter Weel, and Weinberg (2014)).[25] More broadly, teamwork skills may be reflected in traits such as prosociality and sociability (e.g., Kosse and Tincani (2020)). These skills may be productive in interactions with co-workers in teams, but also in interactions with customers, especially where production is customized to specific client needs. They may be particularly relevant in non-routine social interactions that have been found hard to automate so far.

In a model of team production, Deming (2017) depicts social skills as a reduction in the cost of trading tasks between workers. In teams, workers specialize to exploit their comparative advantage in performing different tasks. Social skills reduce coordination costs, allowing workers to specialize and trade more efficiently, increasing the overall output of team production. As workers' productivity depends on their cognitive skills, reduced trading costs due to social skills create a cognitive-social complementarity.

Earnings have been shown to be positively associated with various measures of teamwork skills and sociability. Using the NLSY79, Deming (2017) measures social skills as the average of four standardized items: self-reported sociability (shyness vs. outgoingness) as young adults and retrospectively at age six, participation in high-school sports, and number of high-school club

[25] See Weidmann and Deming (2021) for further analysis of the skills of team players and how they affect team performance.

participations.[26] Results show positive wage returns to this social skill measure, conditional on cognitive skills (AFQT) and personality traits (Rotter and Rosenberg). Social skills interact positively with cognitive skills (but not with personality traits), indicating complementarity. Deming (2017) also finds that wage returns to social skills increased between the 1980s/1990s and the mid-2000s. For the intertemporal comparison, he measures social skills in the NLSY97 using two Big Five items for extraversion and restricts the NLSY79 measurement to the two sociability items, standardizing both measures in the respective survey. Additional evidence shows that workers with higher social skills tend to sort into occupations that are intensive in tasks that require these skills. Employment and wages grew over time in occupations intensive in social interactions, particularly in occupations that require both high math and social skills.[27]

The skill measurement is similar to earlier work by Borghans, Ter Weel, and Weinberg (2014) who depict 'people skills' by measures of youth sociability in the NLSY79. In a model with individual fixed effects, the premium of people skills increased before 1992 when measured by high-school club participation or self-assessed adult shyness (but not retrospective shyness at age six) and decreased afterwards.

Three European studies (introduced in previous sections) similarly find increasing returns to social skills over time. Edin et al. (2022) find that returns to noncognitive skills increased in Sweden between 1992 and 2013. They interpret their measure as capturing teamwork and leadership skills, but it may also reflect other aspects of "the objective of the [psychologist] interview [which] is to assess the conscript's ability to cope with the psychological requirements of the military service and, in the extreme case, war" (Lindqvist and Vestman (2011)). Izadi and Tuhkuri (2024) interpret two personality traits contained in the test of Finnish conscripts – sociability and activity – as measures of extraversion. They find that returns to extraversion increased from 2001 to 2015, whereas returns to consciousness remained stable. The increasing returns to extraversion are driven by workers at the lower end of the earnings distribution and by increases in employment (rather than income conditional on employment). Their analysis

[26] The use of participation in high-school sports and clubs relates back to earlier work showing positive associations with labor market outcomes (e.g., Barron, Ewing, and Waddell (2000); Persico, Postlewaite, and Silverman (2004); Kuhn and Weinberger (2005); Stevenson (2010)).

[27] Aghion et al. (2023) argue that teamwork and co-worker communication can also be important for workers with low formal education. While they cannot link skill measures to individual earnings in their UK matched employer-employee panel data, they show that wages of low-educated workers increase more steeply with tenure if they work in occupations where social skills are more important.

suggests decreasing cognitive-noncognitive complementarity. Navarini (2023) finds increasing returns to social skills in Germany between cohorts born in 1987-1995 and 1996-2003. The latent social skill factor is meant to capture an externalizing factor linked to sociability and extraversion, as distinct from a diligence factor. The increases in returns to social skills are driven by increasing social-cognitive complementarities at the upper tail of the skill distribution.

Turning to the broader concept of prosociality, Kosse and Tincani (2020) find a significant income premium for prosociality in a global study pooling 76 countries. Using the Global Preference Survey (Falk et al. (2018)), their prosociality measure reflects the first principal component of three preference measures: altruism, positive reciprocity, and trust. The income premium for prosociality does not differ systematically by continent or development level, although there is heterogeneity across countries, and a few countries even show negative associations. Income associations are stronger for reciprocity and altruism than for trust.

While causality is hard to establish in observational data, resume experiments show that signals of social skills affect the first step to labor market success, being invited for a job interview. In a Belgian field experiment, Baert and Vujić (2018) find that volunteer activities randomly varied on resumes of applicants to vacancies in specific white-collar occupations increase the likelihood of positive employer reactions. Heinz and Schumacher (2017) show that subjects who report social engagement on their resume indeed contribute more in a public good game, and that human resource managers can predict subjects' behavior in the game based on the mentioning of social engagement in resumes. These results indicate that social engagement is indeed effectively used as a signal for willingness to cooperate in teams. In a resume experiment with German human resource managers, Piopiunik et al. (2020) find that social volunteering positively affects job-interview invitations for secondary-school graduates who apply for apprenticeships, whereas mentioning team sports (as opposed to single sports) increases invitations for college graduates who apply for business trainee positions.

Overall, the evidence shows that different facets of social skills have relevance for earnings generation, consistent with their value as basic skills that make interpersonal interactions within teams and with customers more efficient. However, interpretation is impaired because available measurements capture the different underlying concepts to varying extent. Rather than extensive assessments of well-defined skill dimensions, work on social skills often reverts to simple indicators of youth activities, latent factors extracted from item batteries that are hard to interpret as specific skills, or simple signals on worker resumes. When comparing estimates over time, lack of consistent measurement of social skills generally requires standardization of measures within periods, implicitly assuming constant variance in social skills in the population. But an increasing estimate on a standardized measure could also reflect that the variance in the true underlying variable increased over time (see Section 2.3).[28] The variation in social skills may also evolve differently from their pre-market observation to the earnings observation.

## 6. Skill Mismatch with Several Skill Dimensions

Studying a single skill dimension at a time may miss important aspects of how skills affect labor market outcomes. Not only can various skill dimensions be correlated and interact in earnings determination. Workers with different skills may also sort into jobs that entail different tasks. The process of matching workers to jobs that both differ along various skill/task dimensions opens the possibility of mismatch between supplied and demanded skills (Lise and Postel-Vinay (2020); Guvenen et al. (2020)).[29] While the analyses discussed so far usually focus on one particular skill aspect, several in fact incorporate more than one skill dimension, usually one cognitive and one noncognitive.[30]

To measure several skill dimensions for use in structural models of search and matching, recent research applies PCA to underlying skill measures in the NLSY79. For example, Lise and Postel-Vinay (2020) derive measures of cognitive, interpersonal, and manual skills using exclusion restrictions about which underlying measures – tests of aptitude, locus of control, self-esteem, measures of criminal behavior and health, and occupational requirements of education – load on which skill dimension. Guvenen et al. (2020) take the first principal components of selected subsets of measures that they interpret as verbal, math, and social skills.[31]

The estimated models produce patterns of (mis)match between workers' accumulated and jobs' required skills consistent with the importance of considering skill multidimensionality for

[28] Changes in the variance of skills have been little studied, but significant trends in skill levels have been documented for cognitive skills, personality traits, leadership, and sociability (e.g., Jokela et al. (2017)).

[29] Similarly, Acemoglu and Autor (2012) argue that "acknowledging the multifaceted nature of human capital and understanding how it is allocated to a changing set of tasks" broadens and strengthens the argument of what human capital does in the labor market.

[30] E.g., Heckman, Stixrud, and Urzua (2006), Lindqvist and Vestman (2011), Weinberger (2014), Deming (2017), Piopiunik et al. (2020), and Edin et al. (2022).

[31] In a similar spirit, Baley, Figueiredo, and Ulbricht (2022) reduce the same underlying data into four skill dimensions – math, verbal, social, and technical skills – to study the cyclicality of skill mismatch.

labor market careers. Lise and Postel-Vinay (2020) develop a search model with multiple skills and occupation-specific learning by doing. In their quantitative model, cognitive skills have the highest return, but they are not easy to accumulate and therefore slow to adjust to career shocks. By contrast, manual skills have only moderate returns, but they adjust more quickly with (non-)usage. Interpersonal skills have slightly higher returns than manual skills and hardly change over the lifecycle. The estimated cost of mismatch is much higher for cognitive skills than for the other two skill dimensions, especially when underqualified for job requirements.

Relatedly, Guvenen et al. (2020) derive a summary measure of multidimensional skill mismatch between workers and occupations from a lifecycle model of occupational choice and skill acquisition in which workers learn about their ability to acquire different skills. They find that mismatch decreases both the level and trajectory of earnings with occupational tenure and exerts cumulative scarring effects in subsequent jobs. The association of mismatch with earnings is stronger for math and verbal skills than for social skills.[32]

In these applications, the dimensionality reduction of underlying skill indicators into three dimensions allows for a richer analysis of the relevance of skill multidimensionality than previous approaches. Still, the consideration of three skill dimensions does not fully match the multitude of job tasks considered in the basic task framework (see Section 2.1).

## 7. Multidimensional Skill Measurement in Large Online Data Sources

Recently, two types of contributions have moved the analysis of skills and earnings closer to a multidimensional perspective by drawing on big data applications that make non-traditional, unstructured online data sources usable. Job vacancies posted by employers allow to observe many skill categories on the demand side (Section 7.1). Social media platforms for professional networking allow text analyses of worker skills on the supply side (Section 7.2). On the basic-applied continuum (see Section 2.2), both approaches move towards more applied skills that can be directly employed to perform job tasks.

### 7.1 Skill Requirements in Job Vacancy Postings

Recent work uses advertisements of vacancies that firms post on online job boards or their own websites to derive new skill measures. Using text analysis tools, measures of various skill

[32] See Yamaguchi (2012) and Lindenlaub (2017) for related prior work on multidimensional skills and tasks.

categories are derived from the vast amount of skill requirement information that firms indicate in open text fields of the postings. This richer depiction of skills comes from the demand side, capturing skill dimensions that firms desire for jobs that they would like to fill.

The most commonly used database of job postings is provided by the employment analytics firm Burning Glass Technologies (now Lightcast). The firm compiles job ad data from various online sources into a structured database. It uses machine-learning algorithms to derive over 10,000 keywords and phrases from the ad texts that are interpreted as job requirements. Deming and Kahn (2018) use these data to derive ten categories of job skills, specifying keywords that define each category in ways motivated by the task framework. For example, an ad is classified as demanding cognitive skills if it contains any of the following words: problem solving, research, analytical, critical thinking, math, or statistics. Social skills are classified by the words communication, teamwork, collaboration, negotiation, or presentation. In addition, Deming and Kahn (2018) classify the following skill categories: character, writing, customer service, project management, people management, finance, computer, and software. In Deming and Noray (2020), the classification is revised and extended to 14 skill categories which also include creativity, business systems, technical support, data analysis, and different software and programming categories. Acemoglu et al. (2022) use an extended version of 28 skill categories that mostly specify additional occupational activities.[33]

The skill measures derived from job postings have significant explanatory power for various wage and performance measures beyond the usual measures contained in earnings analyses. Because most job ads do not post information on offered wages, Deming and Kahn (2018) study average wages in the Occupational Employment Statistics for over 50,000 cells defined by metropolitan statistical areas (MSAs) and six-digit occupations in the Standard Occupational Classification (SOC). They focus on professional occupations (ten of the 23 major SOC groups) and use a cross-section of job ad data in 2010-2015. Conditional on years of education and experience, average wages at the location-occupation level are positively associated with the shares of job ads requiring cognitive and social skills. They are also associated with the share requiring both skill types, suggesting cognitive-social complementarity. The authors note that the

[33] Langer and Wiederhold (2023) and Lipowski, Salomons, and Zierahn-Weilage (2024) use similar approaches to characterize skill requirements in German apprenticeship curricula.

other eight skill categories, while not shown, have additional explanatory power. Average skill requirements are also associated with Compustat measures of firm performance.

Using data on firms' salary offers in a subset of 12.2 (out of 190.2) million ads in 2016-2019, Alekseeva et al. (2021) estimate premia to various skill categories – AI skills and the ten Deming and Kahn (2018) categories – at the job-ad level. AI skills, as well as cognitive and social skills, have positive wage premia. Skill categories such as project and people management, finance and accounting, and software skills also capture positive wage premia, whereas others such as computer, character, and customer service skills show negative estimates.

Crafting eleven skill categories, Hemelt et al. (2023) show that differences in employers' skill demand across college majors account for considerable wage variation across MSA-major cells. Josten et al. (2024) study MSCI-World-listed companies in another job ad platform, LinkUp Raw. Using PCA to derive nine latent skill groups, they find that changes in wage premia between 2014-2015 and 2018-2020 (in state by six-digit occupation cells) differ within broad skill categories. For example, within interpersonal skills, skills labelled 'collaborative leader' show positive and increasing wage premia, whereas 'interpersonal and organized' is negatively associated with wages. Within data-science skills, the latest skill types show positive premia whereas previous skill vintages turn from positive to negative. Interaction analysis suggests that 'collaborative leader' and 'research' skills interact positively.[34]

While the job ad data allow for a much richer depiction of the multidimensionality of applied skills, they also come with limitations. Because of labor market mismatch (see Section 6), many vacancies may not be filled with workers who have (all) the desired skills. Advertised job positions may not even be filled at all. As vacancy postings refer to jobs, not workers, it is difficult to separate job requirements from worker skills, similar to the O*NET descriptions of occupational tasks (Sanders and Taber (2012)). In consequence, the approach provides better measures for firms' skill demands than for workers' supplied skills or for the labor market equilibrium. The skill requirements from job postings cannot generally be linked to individual backgrounds or outcomes of workers. In addition, job ads do not reflect the stock of current workers but the flow of new workers to be hired.

[34] Several papers use the job ad data to study various labor market aspects such as changing skill requirements in the great recession (Hershbein and Kahn (2018); Modestino, Shoag, and Ballance (2016, 2020); Blair and Deming (2020)), occupational dynamics (Deming and Noray (2020)), within-occupation task transformation (Atalay et al. (2020)), AI exposure (Acemoglu et al. (2022)), and job losses (Braxton and Taska (2023)).

### 7.2 Skills Reported in Professional Profiles on Networking Platforms

Another way to measure a multitude of skills is to utilize professional profiles that workers post on online networking platforms. These profiles provide uniquely extensive data on self-reported skills for individual workers that can be linked to their career development. This approach is employed by Dorn et al. (2024), who analyze skill data from professional profiles of over 8 million U.S. college graduates publicly available on LinkedIn, the world's largest social media platform for professional networking and career development. Their approach takes the definition and dimensionality of valuable skills from the decisions that workers make about what to report on their public profiles. The raw database of scraped public profiles is provided and curated by Revelio Labs, a workforce intelligence company. The firm also imputes earnings based on information on job titles, companies, locations, and other information using a proprietary salary model that is trained on external sources such as visa applications and databases of self-reported salaries. Using professional profiles overcomes the drawbacks of job postings that depict the demand side but cannot link desired skills to actual workers.

Using a word association algorithm, the over 10,000 different original text strings of reported skills are aggregated into 48 skill clusters that suggest a richness of multidimensional worker skills not usually captured by the alternative approaches. The covered skill clusters tend to depict various applied skills that can be directly used to perform occupational tasks. Some skill clusters are rather occupation-specific such as particular software, legal, biotechnological, or medical skills, whereas others can be applied more generally across occupations such as program management, business analysis, team leadership, or public speaking.

Dorn et al. (2024) find that workers who report more skills on their LinkedIn profiles tend to have jobs that pay substantially higher earnings. Job-based earnings also differ with the skill composition, increasing in the shares of occupation-specific (rather than general) and managerial skills. Skill clusters that show particularly strong positive associations with job-based earnings include financial-analysis, legal, strategic-planning, medical, software-development, and marketing skills. Other skill clusters are more weakly associated with earnings, and some clusters such as customer-service and communication skills even show negative associations, indicating that these generic clusters may not qualify workers for particularly highly paid jobs.

Even though the self-reported skill measures are likely quite noisy measures of workers' actual human capital, they can account for a larger fraction of variation in job-based earnings than augmented Mincer models with detailed vectors of education and experience variables including field of study and college quality. The skill measures capture substantial earnings variation that is not captured by the conventional human capital proxies and mediate an important part of their association with earnings.

These results suggest that previous work using lower-dimensional measures of workers' skill sets may miss important aspects of the role of skills in determining earnings. The skill measures derived from professional profiles are only noisy measures of workers' actual skill sets. They are neither validated nor employ a common scale and do not measure any given skill dimension as deeply as detailed assessments developed particularly for the purpose. Although it is possible to count the number of skills mentioned in a given cluster, they miss much of the potentially relevant variation in the intensity of skill possession. They also provide only one snapshot of skill relevance in the current labor market; as contexts of supply and demand change, applied vocational skills may become obsolete more quickly than more basic skills (Hanushek et al. (2017b)). Despite these limitations, the results indicate that the importance of worker skills in the labor market may be richer than suggested by generally available measures.

## 8. Discussion and Conclusion

Investigation of the relationship between multidimensional skills and earnings is very much work in progress. As has become obvious in this review, disparate strands of literature that study aspects of skills and earnings use quite different approaches and thus do not lend themselves easily for a fully integrated treatment. No study so far provides an exhaustive multidimensional perspective that encompasses all the skill dimensions explored in the literature.

The available evidence permits some broad conclusions. At the most general level, there are earnings premia for skills in all three basic-skill categories – cognitive, personality, and social. Numeracy and literacy, conscientiousness and internal locus of control, and leadership and teamwork are examples of skill dimensions in each category that have been shown to pay off in the labor market. Data from job postings and professional profiles capture a much broader spectrum of applied skills that account for substantial earnings variation. At the same time, the scope of what we do not know is substantial. All analyses have evident limitations, partly related to their lack of interconnectedness. A more comprehensive depiction of the earnings implications of multidimensional skills also requires a better understanding of the respective contexts defined by skill supply and demand and the implied scarcity of various skill dimensions, the matching of worker skills to job tasks, the interactions and complementarities between different skill dimensions, and the basic-applied relationship. These limitations should motivate future analyses that better integrate the available perspectives and insights in the literature. An integrated perspective will hopefully be facilitated by bringing various approaches together in one place and by adopting a conceptual framework that explicitly differentiates between basic and applied skills. However, addressing the limitations will also require new directions that take a genuinely multidimensional perspective on the role of skills in earnings generation.

The obstacles to progress partly reflect challenges in the measurement of multiple skills. The indicated importance of measurement error underscores that improved measurement should be high on the agenda of future research. Cognitive skills are not as well captured by ultra-short IQ tests as by extensive testing of specific domains. Personality and social skills can be measured by a few self-reported items or extensive psychological batteries and behavioral assessments. Crucially, a comprehensive analysis of how multidimensional skills interact to influence earnings necessitates observing a broad array of skill dimensions in a single setting. Still, the reviewed work suggests that efforts to measure the multidimensionality of skills are likely to yield a more informative picture of workers' relevant human capital than traditional metrics such as years of education, not least because the amount and composition of skills gained per school year can vary significantly by context and over time (as Covid has made painfully clear).

Arguably, the most significant challenge lies in establishing causality in the relationships between various skills and earnings. Identification from randomized treatment assignments is difficult to envision in this setting, particularly due to ethical concerns associated with depriving a control group of valuable skills. Furthermore, it is challenging to conceive interventions that trigger only one skill dimension without affecting other dimensions, at least partially. Similarly, most shocks that might give rise to arguably exogenous variation in skills within observational data are likely to affect several skill dimensions simultaneously. Despite these obstacles, careful consideration of potential sources of exogenous variation and the joint consideration of various skill dimensions will help to advance causal inference in the field.

With a better understanding of how different skills affect earnings, the next question will be how best to foster these skills. While a broad literature studies determinants of cognitive skills in schools, much less is known about how personality and social skills can be effectively developed, not least because of limitations in defining and measuring these concepts and in understanding which components are actually relevant. Further questions relate to how both basic and applied skills can be conveyed and stimulated during adulthood.

Technological change continuously alters the job tasks that firms demand workers to perform. Machines, computers, and algorithms replace various – particularly routine – tasks previously performed by workers, while simultaneously requiring workers to perform new tasks that complement the emerging technologies. These developments have changed and will continue to change the demand for various dimensions of skills differently, rendering some skill dimensions obsolete while increasing the scarcity of others. Workers will adjust the skills they acquire and supply in response to these trends. Ongoing debates, particularly concerning advancements in AI, focus on how new technologies will impact the types of skills that yield labor market rewards in the future. The answer will largely depend on the extent to which different skills will turn out to be substitutes or complements to the emerging AI technologies. There are so many open questions about how current and future technological trends will affect the labor market opportunities of different workers. Addressing these questions will be so much more productive if framed in terms of skills that come in many dimensions – basic and applied; cognitive, personality, and social; established and new; mid- and high-level – rather than merely in terms of holding a college degree.

## References


Acemoglu, Daron, David Autor (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, *Volume 4b,* edited by Orley Ashenfelter, David Card. Amsterdam: North Holland: 1043-1171.

Acemoglu, Daron, David Autor (2012). What Does Human Capital Do? A Review of Goldin and Katz's the Race between Education and Technology. *Journal of Economic Literature* 50 (2): 426-463.

Acemoglu, Daron, David Autor, Jonathon Hazell, Pascual Restrepo (2022). Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics* 40 (S1): S293-S340.

Acemoglu, Daron, Pascual Restrepo (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review* 108 (6): 1488-1542.

Acemoglu, Daron, Pascual Restrepo (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica* 90 (5): 1973-2016.

Aghion, Philippe, Antonin Bergeaud, Richard Blundell, Rachel Griffith (2023). Social Skills and the Individual Wage Growth of Less Educated Workers. IZA Discussion Paper 16456. Bonn: IZA Institute of Labor Economics.

Alekseeva, Liudmila, José Azar, Mireia Giné, Sampsa Samila, Bledi Taska (2021). The Demand for AI Skills in the Labor Market. *Labour Economics* 71: 102002.

Almlund, Mathilde, Angela L. Duckworth, James Heckman, Tim Kautz (2011). Personality Psychology and Economics. In *Handbook of the Economics of Education, Vol. 4*, edited by Eric A. Hanushek, Stephen Machin, Ludger Woessmann. Amsterdam: North Holland: 1-181.

Altonji, Joseph G., Peter Arcidiacono, Arnaud Maurel (2016). The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects. In *Handbook of the Economics of Education*, *Vol. 5*, edited by Eric A. Hanushek, Stephen Machin, Ludger Woessmann. Amsterdam: North Holland: 305-396.

Altonji, Joseph G., Erica Blom, Costas Meghir (2012). Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers. *Annual Review of Economics* 4: 21.1-21.39.

Altonji, Joseph G., Charles R. Pierret (2001). Employer Learning and Statistical Discrimination. *Quarterly Journal of Economics* 116 (1): 313-350.

Andrisani, Paul J. (1977). Internal-External Attitudes, Personal Initiative, and the Labor Market Experience of Black and White Men. *Journal of Human Resources* 12 (3): 308-328.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, Daniel Tannenbaum (2020). The Evolution of Work in the United States. *American Economic Journal: Applied Economics* 12 (2): 1-34.

Autor, David, Caroline Chin, Anna Salomons, Bryan Seegmiller (2024). New Frontiers: The Origins and Content of New Work, 1940–2018. *Quarterly Journal of Economics* 139 (3): 1399-1465.

Autor, David, Claudia Goldin, Lawrence F. Katz (2020). Extending the Race between Education and Technology. *AEA Papers and Proceedings* 110: 347-351.

Autor, David H. (2014). Skills, Education, and the Rise of Earnings Inequality among the “Other 99 Percent”. *Science* 344 (843): 843-851.

Autor, David H. (2022). The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty. NBER Working Paper 30074. Cambridge, MA: National Bureau of Economic Research.

Autor, David H., David Dorn (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review* 103 (5): 1553-1597.

Autor, David H., Frank Levy, Richard J. Murnane (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118 (4): 1279-1333.

Avvisati, Francesco, Pauline Givord (2023). The Learning Gain over One School Year among 15-Year-Olds: An International Comparison Based on PISA. *Labour Economics* 84: 102365.

Baert, Stijn, Sunčica Vujić (2018). Does It Pay to Care? Volunteering and Employment Opportunities. *Journal of Population Economics* 31 (3): 819-836.

Baley, Isaac, Ana Figueiredo, Robert Ulbricht (2022). Mismatch Cycles. *Journal of Political Economy* 130 (11): 2943-2984.

Barrick, Murray R., Michael K. Mount (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. *Personnel Psychology* 44 (1): 1-26.

Barron, John M., Bradley T. Ewing, Glen R. Waddell (2000). The Effects of High School Athletic Participation on Education and Labor Market Outcomes. *Review of Economics and Statistics* 82 (3): 409-421.

Beaudry, Paul, David A. Green, Benjamin M. Sand (2016). The Great Reversal in the Demand for Skill and Cognitive Tasks. *Journal of Labor Economics* 34 (S1): S199-S247.

Becker, Anke, Thomas Deckers, Thomas Dohmen, Armin Falk, Fabian Kosse (2012). The Relationship between Economic Preferences and Psychological Personality Measures. *Annual Review of Economics* 4: 453-478.

Becker, Gary S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. New York, NY: National Bureau of Economic Research.

Bishop, John H. (1989). Is the Test Score Decline Responsible for the Productivity Growth Decline? *American Economic Review* 79 (1): 178-197.

Blair, Peter Q., David J. Deming (2020). Structural Increases in Demand for Skill after the Great Recession. *AEA Papers and Proceedings* 110: 362–65.

Blau, Francine D., Lawrence M. Kahn (2005). Do Cognitive Test Scores Explain Higher US Wage Inequality? *Review of Economics and Statistics* 87 (1): 184-193.

Böhlmark, Anders, Matthew J. Lindquist (2006). Life-Cycle Variations in the Association between Current and Lifetime Income: Replication and Extension for Sweden. *Journal of Labor Economics* 24 (4): 879-896.

Borghans, Lex, Angela Lee Duckworth, James J. Heckman, Bas ter Weel (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources* 43 (4): 972-1059.

Borghans, Lex, Bas Ter Weel, Bruce A. Weinberg (2014). People Skills and the Labor-Market Outcomes of Underrepresented Groups. *ILR Review* 67 (2): 287-334.

Bowles, Samuel, Herbert Gintis (1976). *Schooling in Capitalist America: Educational Reform and the Contradictions of Economic Life*. New York: Basic Books.

Bowles, Samuel, Herbert Gintis (2002). Schooling in Capitalist America Revisited. *Sociology of Education* 75 (1): 1-18.

Bowles, Samuel, Herbert Gintis, Melissa Osborne (2001a). The Determinants of Earnings: A Behavioral Approach. *Journal of Economic Literature* 39 (4): 1137-1176.

Bowles, Samuel, Herbert Gintis, Melissa Osborne (2001b). Incentive-Enhancing Preferences: Personality, Behavior, and Earnings. *American Economic Review, AEA Papers and Proceedings* 91 (2): 155-158.

Braxton, J. Carter, Bledi Taska (2023). Technological Change and the Consequences of Job Loss. *American Economic Review* 113 (2): 279-316.

Caplin, Andrew, David J. Deming, Søren Leth-Petersen, Ben Weidmann (2024). Economic Decision-Making Skill Predicts Income in Two Countries. NBER Working Paper 31674. Cambridge, MA: National Bureau of Economic Research.

Card, David (1999). The Causal Effect of Education on Earnings. In *Handbook of Labor Economics*, edited by Orley Ashenfelter, David Card. Amsterdam: North-Holland: 1801-1863.

Castex, Gonzalo, Evgenia Kogan Dechter (2014). The Changing Roles of Education and Ability in Wage Determination. *Journal of Labor Economics* 32 (4): 685-710.

Chetty, Raj, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, Danny Yagan (2011). How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star. *Quarterly Journal of Economics* 126 (4): 1593-1660.

Dahl, Gordon B., Dan-Olof Rooth, Anders Stenberg (2023). High School Majors and Future Earnings. *American Economic Journal: Applied Economics* 15 (1): 351-382.

Deming, David J. (2017). The Growing Importance of Social Skills in the Labor Market. *Quarterly Journal of Economics* 132 (4): 1593-1640.

Deming, David J. (2021). The Growing Importance of Decision-Making on the Job. NBER Working Paper 28733. Cambridge, MA: National Bureau of Economic Research.

Deming, David J. (2023). Multidimensional Human Capital and the Wage Structure. In *Handbook of the Economics of Education, Vol. 7*, edited by Eric A. Hanushek, Stephen Machin, Ludger Woessmann. Amsterdam: North Holland: 469-504.

Deming, David J., Kadeem Noray (2020). Earnings Dynamics, Changing Job Skills, and Stem Careers. *Quarterly Journal of Economics* 135 (4): 1965-2005.

Deming, David, Lisa B. Kahn (2018). Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. *Journal of Labor Economics* 36 (S1): S337-S369.

Dorn, David, Florian Schoner, Moritz Seebacher, Lisa Simon, Ludger Woessmann (2024). Multidimensional Skills as a Measure of Human Capital: Evidence from LinkedIn Profiles. Mimeo. Munich: ifo Institute at the University of Munich.

Duncan, Greg J., James N. Morgan (1981). Sense of Efficacy and Subsequent Change in Earnings-a Replication. *Journal of Human Resources* 16 (4): 649-657.

Edin, Per-Anders, Peter Fredriksson, Martin Nybom, Björn Öckert (2022). The Rising Return to Noncognitive Skill. *American Economic Journal: Applied Economics* 14 (2): 78-100.

Edwards, Richard C. (1976). Individual Traits and Organizational Incentives: What Makes a "Good" Worker? *Journal of Human Resources* 11 (1): 51-68.

Falck, Oliver, Alexandra Heimisch-Roecker, Simon Wiederhold (2021). Returns to ICT Skills. *Research Policy* 50 (7): 104064.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, Uwe Sunde (2018). Global Evidence on Economic Preferences. *Quarterly Journal of Economics* 133 (4): 1645-1692.

Gathmann, Christina, Uta Schönberg (2010). How General Is Human Capital? A Task-Based Approach. *Journal of Labor Economics* 28 (1): 1-49.

Gensowski, Miriam (2018). Personality, IQ, and Lifetime Earnings. *Labour Economics* 51: 170-183.

Goldin, Claudia, Lawrence F. Katz (2008). *The Race between Education and Technology*. Cambridge, MA: Harvard University Press.

Goodman, Joshua (2019). The Labor of Division: Returns to Compulsory High School Math Coursework. *Journal of Labor Economics* 37 (4): 1141-1182.

Griliches, Zvi (1977). Estimating the Returns to Schooling: Some Econometric Problems. *Econometrica* 45 (1): 1-22.

Groves, Melissa Osborne (2005). How Important Is Your Personality? Labor Market Returns to Personality for Women in the US and Uk. *Journal of Economic Psychology* 26 (6): 827-841.

Guvenen, Faith, Burhan Kuruscu, Satoshi Tanaka, David Wiczer (2020). Multidimensional Skill Mismatch. *American Economic Journal: Macroeconomics* 12 (1): 210-244.

Haider, Steven, Gary Solon (2006). Life-Cycle Variation in the Association between Current and Lifetime Earnings. *American Economic Review* 96 (4): 1308-1320.

Hampf, Franziska, Simon Wiederhold, Ludger Woessmann (2017). Skills, Earnings, and Employment: Exploring Causality in the Estimation of Returns to Skills. *Large-scale Assessments in Education* 5 (12): 1-30.

Hanushek, Eric A., Lavinia Kinne, Philipp Lergetporer, Ludger Woessmann (2022). Patience, Risk-Taking, and Human Capital Investment across Countries. *Economic Journal* 132 (646): 2290-2307.

Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, Ludger Woessmann (2015). Returns to Skills around the World: Evidence from PIAAC. *European Economic Review* 73: 103-130.

Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, Ludger Woessmann (2017a). Coping with Change: International Differences in the Returns to Skills. *Economics Letters* 153: 15-19.

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann, Lei Zhang (2017b). General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle. *Journal of Human Resources* 52 (1): 48-87.

Hanushek, Eric A., Yuan Wang, Lei Zhang (2023). Understanding Trends in Chinese Skill Premiums, 2007-2018. NBER Working Paper 31367. Cambridge, MA: National Bureau of Economic Research.

Hanushek, Eric A., Ludger Woessmann (2008). The Role of Cognitive Skills in Economic Development. *Journal of Economic Literature* 46 (3): 607-668.

Hanushek, Eric A., Ludger Woessmann (2011). The Economics of International Differences in Educational Achievement. In *Handbook of the Economics of Education, Vol. 3,* edited by Eric A. Hanushek, Stephen Machin, Ludger Woessmann. Amsterdam: North Holland: 89-200.

Hanushek, Eric A., Lei Zhang (2009). Quality-Consistent Estimates of International Schooling and Skill Gradients. *Journal of Human Capital* 3 (2): 107-143.

Heckman, James J. (1995). Lessons from the Bell Curve. *Journal of Political Economy* 103 (5): 1091-1120.

Heckman, James J., Lance J. Lochner, Petra E. Todd (2006). Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond. In *Handbook of the Economics of Education*, *Vol. 1*, edited by Eric A. Hanushek, Finis Welch. Amsterdam: North Holland: 307-458.

Heckman, James J., Jora Stixrud, Sergio Urzua (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics* 24 (3): 411-482.

Heineck, Guido, Silke Anger (2010). The Returns to Cognitive Abilities and Personality Traits in Germany. *Labour Economics* 17 (3): 535-546.

Heinz, Matthias, Heiner Schumacher (2017). Signaling Cooperation. *European Economic Review* 98: 199-216.

Hellerstein, Judith K., Sai Luo, Sergio S. Urzúa (2024). Toward an Understanding of the Returns to Cognitive Skills across Cohorts. NBER Working Paper 32229. Cambridge, MA: National Bureau of Economic Research.

Hemelt, Steven W., Brad Hershbein, Shawn Martin, Kevin M. Stange (2023). College Majors and Skills: Evidence from the Universe of Online Job Ads. *Labour Economics* 85: 102429.

Hermo, Santiago, Miika Päällysaho, David Seim, Jesse M Shapiro (2022). Labor Market Returns and the Evolution of Cognitive Skills: Theory and Evidence. *Quarterly Journal of Economics* 137 (4): 2309-2361.

Hershbein, Brad, Lisa B. Kahn (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review* 108 (7): 1737-1772.

Hoffman, Mitchell, Steven Tadelis (2021). People Management Skills, Employee Attrition, and Manager Rewards: An Empirical Analysis. *Journal of Political Economy* 129 (1): 243-285.

Izadi, Ramin, Joonas Tuhkuri (2024). Evolving Returns to Personality. *Journal of Labor Economics*: forthcoming.

Jencks, Christopher (1979). *Who Gets Ahead? The Determinants of Success in America*. New York, NY: Basic Books.

Joensen, Juanna Schrøter, Helena Skyt Nielsen (2009). Is There a Causal Effect of High School Math on Labor Market Outcomes? *Journal of Human Resources* 44 (1): 171-198.

Joensen, Juanna Schrøter, Helena Skyt Nielsen (2016). Mathematics and Gender: Heterogeneity in Causes and Consequences. *Economic Journal* 126 (593): 1129-1163.

Jokela, Markus, Tuomas Pekkarinen, Matti Sarvimäki, Marko Terviö, Roope Uusitalo (2017). Secular Rise in Economically Valuable Personality Traits. *Proceedings of the National Academy of Sciences* 114 (25): 6527-6532.

Josten, Cecily, Helen Krause, Grace Lordan, Brian Yeung (2024). What Skills Pay More? The Changing Demand and Return to Skills for Professional Workers. IZA Discussion Paper 16755. Bonn: IZA Institute of Labor Economics.

Jovanovic, Boyan (1979). Job Matching and the Theory of Turnover. *Journal of Political Economy* 87 (5): 972-990.

Judge, Timothy A., Amir Erez, Joyce E. Bono, Carl J. Thoresen (2002). Are Measures of Self-Esteem, Neuroticism, Locus of Control, and Generalized Self-Efficacy Indicators of a Common Core Construct? *Journal of Personality and Social Psychology* 83 (3): 693-710.

Katz, Lawrence F., Kevin M. Murphy (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics* 107 (1): 35-78.

Kirkeboen, Lars J., Edwin Leuven, Magne Mogstad (2016). Field of Study, Earnings, and Self-Selection. *Quarterly Journal of Economics* 131 (3): 1057-1111.

Kosse, Fabian, Thomas Deckers, Pia Pinger, Hannah Schildberg-Hörisch, Armin Falk (2020). The Formation of Prosociality: Causal Evidence on the Role of Social Environment. *Journal of Political Economy* 128 (2): 434-467.

Kosse, Fabian, Michela M. Tincani (2020). Prosociality Predicts Labor Market Success around the World. *Nature Communications* 11 (1): 5298.

Kuhn, Peter, Catherine Weinberger (2005). Leadership Skills and Wages. *Journal of Labor Economics* 23 (3): 395-436.

Langer, Christina, Simon Wiederhold (2023). The Value of Early-Career Skills. CESifo Working Paper 10288. Munich: CESifo.

Lazear, Edward P. (2003). Teacher Incentives. *Swedish Economic Policy Review* 10 (3): 179-214.

Leuven, Edwin, Hessel Oosterbeek, Hans van Ophem (2004). Explaining International Differences in Male Skill Wage Differentials by Differences in Demand and Supply of Skills. *Economic Journal* 114 (495): 466-486.

Lindenlaub, Ilse (2017). Sorting Multidimensional Types: Theory and Application. *Review of Economic Studies* 84 (2): 718-789.

Lindqvist, Erik, Roine Vestman (2011). The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment. *American Economic Journal: Applied Economics* 3 (1): 101-128.

Lipowski, Cäcilia, Anna Salomons, Ulrich Zierahn-Weilage (2024). Expertise at Work: New Technologies, New Skills, and Worker Impacts. MIT Shaping the Future of Work Initiative, Working Paper.

Lise, Jeremy, Fabien Postel-Vinay (2020). Multidimensional Skills, Sorting, and Human Capital Accumulation. *American Economic Review* 110 (8): 2328-2376.

Mincer, Jacob (1974). *Schooling, Experience, and Earnings*. New York: NBER.

Modestino, Alicia Sasser, Daniel Shoag, Joshua Ballance (2016). Downskilling: Changes in Employer Skill Requirements over the Business Cycle. *Labour Economics* 41: 333-347.

Modestino, Alicia Sasser, Daniel Shoag, Joshua Ballance (2020). Upskilling: Do Employers Demand Greater Skill When Workers Are Plentiful? *Review of Economics and Statistics* 102 (4): 793-805.

Mueller, Gerrit, Erik Plug (2006). Estimating the Effect of Personality on Male and Female Earnings. *ILR Review* 60 (1): 3-22.

Mulligan, Casey B. (1999). Galton Versus the Human Capital Approach to Inheritance. *Journal of Political Economy* 107 (6, pt. 2): S184-S224.

Murnane, Richard J., John B. Willett, Yves Duhaldeborde, John H. Tyler (2000). How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings? *Journal of Policy Analysis and Management* 19 (4): 547-568.

Murnane, Richard J., John B. Willett, Frank Levy (1995). The Growing Importance of Cognitive Skills in Wage Determination. *Review of Economics and Statistics* 77 (2): 251-266.

Navarini, Lorenzo (2023). Changes in Returns to Multidimensional Skills across Cohorts.

Neal, Derek, William R. Johnson (1996). The Role of Pre-Market Factors in Black-White Differences. *Journal of Political Economy* 104 (5): 869-895.

Nelson, Richard R., Edmund Phelps (1966). Investment in Humans, Technology Diffusion and Economic Growth. *American Economic Review* 56 (2): 69-75.

Nyhus, Ellen K., Empar Pons (2005). The Effects of Personality on Earnings. *Journal of Economic Psychology* 26 (3): 363-384.

OECD (2013). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. Paris: Organisation for Economic Co-operation and Development.

Persico, Nicola, Andrew Postlewaite, Dan Silverman (2004). The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height. *Journal of Political Economy* 112 (5): 1019-1053.

Piopiunik, Marc, Guido Schwerdt, Lisa Simon, Ludger Woessmann (2020). Skills, Signals, and Employability: An Experimental Investigation. *European Economic Review* 123: 103374.

Prevoo, Tyas, Bas ter Weel (2015). The Importance of Early Conscientiousness for Socio-Economic Outcomes: Evidence from the British Cohort Study. *Oxford Economic Papers* 67 (4): 918-948.

Rosenberg, Morris (1965). *Society and the Adolescent Self-Image*. Princeton, NJ: Princeton University Press.

Rotter, Julian B. (1966). *Generalized Expectancies for Internal Versus External Control of Reinforcement*. Washington, DC: American Psychological Association.

Salgado, Jesús F. (1997). The Five Factor Model of Personality and Job Performance in the European Community. *Journal of Applied Psychology* 82 (1): 30-43.

Sanders, Carl, Christopher Taber (2012). Life-Cycle Wage Growth and Heterogeneous Human Capital. *Annual Review of Economics* 4: 399-425.

Schultz, Theodore W. (1961). Investment in Human Capital. *American Economic Review* 51 (1): 1-17.

Schultz, Theodore W. (1975). The Value of the Ability to Deal with Disequilibria. *Journal of Economic Literature* 13 (3): 827-846.

Stevenson, Betsey (2010). Beyond the Classroom: Using Title Ix to Measure the Return to High School Sports. *Review of Economics and Statistics* 92 (2): 284-301.

Tinbergen, Jan (1974). Substitution of Graduate by Other Labour. *Kyklos* 27 (2): 217-226.

Weidmann, Ben, David Deming (2021). Team Players: How Social Skills Improve Team Performance. *Econometrica* 89 (6): 2637-2657.

Weinberger, Catherine J. (2014). The Increasing Complementarity between Cognitive and Social Skills. *Review of Economics and Statistics* 96 (5): 849-861.

Welch, Finis (1970). Education in Production. *Journal of Political Economy* 78 (1): 35-59.

Woessmann, Ludger (2016). The Importance of School Systems: Evidence from International Differences in Student Achievement. *Journal of Economic Perspectives* 30 (3): 3-32.

Yamaguchi, Shintaro (2012). Tasks and Heterogeneous Human Capital. *Journal of Labor Economics* 30 (1): 1-53.