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Skills and human capital in the labor market

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Abstract

This paper synthesizes the economics literature on skills and human capital, with a particular focus on higher-order capacities like social and decision-making skills. We review the empirical evidence on returns to human capital from both a micro and macro perspective, as well as the evidence on returns to human capital investment over the life-cycle. We highlight two key limitations of human capital theory as currently implemented. First, prior work mostly assumes that human capital is one-dimensional and can be measured by education or test scores alone. Second, human capital is typically modeled as augmenting the marginal product of labor with workers being treated as factors of production, just like physical capital. We argue for a new approach that treats workers as *agents* who decide how to allocate their labor over job tasks. Traditional cognitive skills make workers more productive in any task, while higher-order skills govern workers' choices of which tasks to perform and whether to work alone or in a team. We illustrate the value of this approach with stylized models that incorporate teamwork and decision-making skills and generate predictions about how returns to skills vary across contexts.

Keywords: education, skills, human capital, labor market returns
JEL Classification: I26, J2, J31

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1 Introduction

A central area of study in labor economics is the causes of earnings differences between people, and by extension, the structure of wages and earnings in the labor market. As seminal work by Mincer (1958), Becker (1962), and many others has shown, an important predictor of earnings differences between people and across countries is *human capital*. Human capital theory is the idea that investments like education or training which make people more productive are compensated by increased labor market earnings.

Human capital theory explains why education would lead to higher wages in principle. A large literature estimates the returns to education in practice (Mincer, 1974; Lemieux, 2006). Thousands of descriptive and causal studies in settings all around the world estimate that people earn between five and fifteen percent more for each additional year of educational attainment, with an average that centers roughly around ten percent (Card, 1999; Bhuller et al., 2017; Psacharopoulos and Patrinos, 2018; Gunderson and Oreopolous, 2020). Other studies estimate the value of alternative measures of human capital such as cognitive skills or college quality (Hanushek and Woessmann, 2012; Smith et al., 2020). Overall, human capital explains at least one third of the cross-sectional variation in wages between workers in a country (Deming, 2022).

A causal return to schooling of around ten percent per year is not some fundamental law of nature, but rather the result of an equilibrium between the supply of and the demand for skills (Tinbergen, 1974; Katz and Murphy, 1992; Goldin and Katz, 2007). Intuitively, the value of skills learned in school is contextual and depends on economic fundamentals like the technology of workplace production and the broader economic environment. A prominent theory in economics – often called the "canonical model" – helps explain why relative wages for U.S. college graduates rose rapidly in the 1980s and have stayed high through the present day, and why the return to education is higher in countries that have historically invested less in education (e.g. Goldin and Katz 2007; Acemoglu and Autor 2011). Human capital theory also helps explain earnings and productivity differences across countries, although the validity and magnitude of the impact of education on GDP growth in cross-country earnings regressions depends heavily on modeling assumptions (Mankiw et al., 1992; Hall and Jones, 1999; Caselli, 2005; Jones, 2014; Caselli and Ciccone, 2019). Still, the best quasi-experimental evidence suggests that human capital explains at least half of the variation in average earnings across countries (Hendricks and Schoellman, 2018; Deming, 2022).

Human capital theory also delivers important insights about the optimal timing of investments over the life-cycle. Ben-Porath (1967) shows that schooling and other human capital investments are best undertaken early in life, when there is a longer horizon over which to reap benefits. In Cunha and Heckman (2007), early investment is optimal for technological reasons, e.g. "skills beget skills". Nonetheless, Hendren and Sprung-Keyser (2020) find high returns to human capital investment in early childhood but also later in life, through young adulthood.

Human capital theory has been influential not only within economics, but also in the wider world of policy and practice. Global educational attainment has increased dramatically since Mincer (1958) and Becker (1962). Today, more than half the world's adults have completed secondary schooling, up from just 13 percent in 1950. Over the same time period, the share of adults with tertiary degrees has grown by a multiple of seven, such that fourteen percent of adults have completed tertiary education (Lee and Lee, 2016). This comes at no small cost. Across the OECD, countries spend nearly five percent of their GDP on education (OECD, 2023).

In this paper we argue that despite its stunning success, a richer and more flexible conceptualization of human capital is needed to explain recent trends in the labor market. Since 2000 the economic returns to cognitive skills have declined in the U.S., Sweden, and Finland, despite the fact that the demand for college-educated labor grew over this period (Castex and Kogan Dechter, 2014; Edin et al., 2022; Izadi and Tuhkuri, 2024). Returns to various measures of "non-cognitive" or "soft" skills like conscientiousness, extraversion, emotional stability, and social skills have grown markedly over the same period (Deming, 2017; Edin et al., 2022; Izadi and Tuhkuri, 2024). Yet despite growing evidence of the economic importance of what Deming (2022) calls "higher-order" skills, we have little conceptual understanding of what these skills are and how to measure and develop them.

We highlight two key limitations of human capital theory as it is currently implemented. First, prior work mostly assumes that human capital is one-dimensional and can be measured by years of education, test scores, or some other attribute. This single index view of human capital is necessary for tractability in the canonical model of Goldin and Katz (2007) and the task framework of Acemoglu and Autor (2011), among others.[1] Second, human capital is typically treated as augmenting the marginal product of labor in an aggregate or firm-specific production function. Workers are assigned to jobs or tasks by firms in an exact analogy to physical capital.[2]

We argue that higher-order skills are best understood in a context where workers are not just factors of production, but rather agents who make choices and respond to incentives. Traditional human capital is *productive* in the sense that it augments the marginal product of labor. However when workers are agents, they must also decide how to allocate their labor over tasks and whether to work alone or with others. We argue for a framework where traditional cognitive skills augment the marginal product of labor in tasks and "higher-order" skills govern the choice of tasks. We illustrate the value of this approach by developing simplified versions of the models in Deming (2017) and

[1] A few papers develop and empirically estimate models where human capital is a multi-dimensional vector of skills with weights that differ over time and across occupations and industries (Heckman, 2006; Sanders and Taber, 2012; Lise and Postel-Vinay, 2020; Guvenen et al., 2020).

[2] Acemoglu and Autor (2011) allow workers to be assigned to different tasks endogenously, but the assignment depends on the economic environment rather than workers' choices.

Caplin et al. (2023).

The paper proceeds as follows. Section 2 provides a whirlwind tour of the literature of seminal work on the relationship between human capital and earnings, with a particular focus on reconciling micro and macro estimates. Section 3 reviews the literature on human capital investment and development and attempts to reconcile classic theoretical results with recent empirical evidence. Section 4 discusses the intellectual origins of multidimensional human capital and reviews recent research on the economic value of higher-order (sometimes called "non-cognitive", or "soft") skills. Section 5 develops models of the value of decision-making and social skills where workers make choices over tasks, and discusses possible extensions of this idea to other higher-order skills. Section 6 concludes.

2 Economic returns to human capital

2.1 Microeconomic estimates

Mincer (1974) develops a formal model where identical workers invest in human capital to maximize future earnings and derives this relationship, known colloquially as the "Mincer equation":

$$lnY_i = \alpha + \beta Schooling_i + f(Experience_i) + \epsilon_i. \tag{1}$$

The Mincer equation regresses the log of individual earnings on years of education (schooling) and a flexible function of labor market experience. The coefficient β measures the percent increase in wages associated with an additional year of education.

The core insights of the Mincer model have largely withstood the test of time (Lemieux, 2006). Psacharopoulos and Patrinos (2018) compile 1,120 estimates of the returns to education from 139 countries since 1950, and find that the private average return to education is around nine percent per year of education, with typical estimates in the range between five and fifteen percent (Gunderson and Oreopolous, 2020; Patrinos and Psacharopoulos, 2020). In the United States, differences in education explain roughly a third of the variation in cross-sectional earnings (Card, 1999; Deming, 2022).

One obvious issue is that people who expect to earn higher returns will invest more in schooling, and thus comparisons between people with different levels of education suffer from "ability bias" (Griliches, 1979; Card, 1999). Labor economists have overcome this problem with various quasi-experimental approaches. These include finding instrumental variables (IVs) that affect schooling but are arguably unrelated to ability or other predictors of earnings such as compulsory schooling laws, school construction, and changes in education funding (Angrist and Krueger, 1991; Duflo, 2001; Oreopoulos, 2006; Khanna, 2023) and exploiting discontinuous changes in the probability of admission around grade or test thresholds. These so-called "regression discontinuity" (RD) designs have become common in recent years, and have been used to estimate returns to education in the United States, Sweden, China, South Korea, and Finland (Hoekstra, 2009; Öckert, 2010; Zimmerman, 2014; Fan et al., 2018; Ost et al., 2018; Smith et al., 2020; Kim, 2021; Kozakowski, 2023; Mountjoy, 2024; Virtanen et al., 2024).

IV and RD designs yield causal estimates, but typically for a selected subset of some larger population. For example, RD estimates apply only to those who were barely rejected or admitted, and may not generalize to the broader population. Despite this limitation, estimates of the return to education from quasi-experimental studies are surprisingly similar to each other and to naive estimates from the Mincer model.[3] Across a large range of research designs, places, and periods of time, the return to a year of education seems to be around ten percent.

Of course, human capital encompasses much more than just the quantity of education. The quality of education likely varies a lot between workers with the same level of educational attainment (Card, 1993; Carneiro et al., 2011). More generally, human capital includes any attribute that makes people more productive in the labor market, including business acumen, health, and other factors (Schultz, 1961; Becker, 2007; Smith et al., 2019). Smith et al. (2019) find that 75 percent of private pass-through business profit is attributable to the owner's human capital rather than physical or financial assets, and variance decompositions of earnings in matched employer-employee data find that "worker effects" account for nearly half of the variance of earnings (Card et al., 2018; Song et al., 2019). These studies, which account for all measured and unmeasured forms of human capital, typically find that human capital explains half or more of earnings variation.

One potential concern is that schooling signals higher productivity but does not directly cause it (Spence, 1974; Caplan, 2019). However, many studies find positive returns to additional years of education that are not directly observed by employers, and therefore cannot act as signals. Compulsory schooling laws and school construction programs both increased primary and secondary school enrollment and earnings without leading to large increases in degree attainment (Angrist and Krueger, 1991; Duflo, 2001). Other studies find large labor market returns to coursework and specific skills among people with the same degree (Arteaga, 2018; Goodman, 2019). Although it is difficult to distinguish empirically between human capital and signaling, a particularly clever study by Aryal et al. (2022) uses the differential observability of compulsory schooling laws across regions in Norway to separate human capital from signaling. They estimate that human capital accounts for

[3]For example, Zimmerman (2014) uses an RD design for public universities in Florida and finds a return of about 10 percent to an additional year of four-year college. Duflo (2001) studies a massive school construction program in Indonesia, and finds returns to education between seven and ten percent. Khanna (2023) studies a school construction program in India and estimates average returns to schooling of about thirteen percent (Khanna, 2023). Oreopoulos (2006) compares cohorts in the United Kingdom who are born right before versus right after the changes in the school-leaving-age, and finds that an additional year of education results in ten to fourteen percent higher earnings

around 70 percent of the return to secondary school education.

2.2 Human capital and the wage structure

The causal impact of education on earnings is one of the most well-established findings in social science. But why do empirical estimates so often center around 10 percent? More importantly, what explains the temporal and cross-country variation in returns to education? An important literature in economics argues that the return to human capitalvand the overall wage structure of an economy is determined by the equilibrium between the supply of and the demand for skills.

The intellectual origins of this literature begin with the "education race" idea advanced first by Tinbergen (1974). Tinbergen (1974) argued that the path of income inequality "depends on the 'race' between third-level (e.g. college-educated) manpower due to technological development and supply of it due to increased schooling". Katz and Murphy (1992) and Goldin and Katz (2007) mathematically formalize and empirically test the "education race" model and find that it does a remarkably good job of explaining fluctuations in the average return to education in the U.S. over nearly a century. Because this basic supply-demand model has been so influential and has explained the U.S. wage structure so well, Acemoglu and Autor (2011) began referring to it as the "canonical model".

The canonical model begins with an aggregate production function for a single composite good Y. Y is produced using only two factors, low- and high-skilled labor (L and H respectively). Workers supply labor inelastically and the economy is closed and perfectly competitive, so that all workers are paid their marginal product of labor.

An important feature of the canonical model is that worker skill groups are imperfect substitutes in production. A natural interpretation is that they work in different types of occupations which are needed in some combination to produce total output. The aggregate production function has a constant elasticity of substitution (CES) function, as pictured in Equation 2:

$$Y = [(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

where $\sigma \to 0$ is the elasticity of substitution between worker skill groups, and A_H and A_L are technology terms that augment the productivity of each skill group.

As $\sigma \to \infty$, L and H are perfect substitutes, which means that relative skill supplies don't matter and micro estimates of the return to education could scale up infinitely. To see this we can derive the skill premium ω as the relative wage for type H workers:

$$\ln \omega = \ln\left(\frac{w_H}{w_L}\right) = \ln\left(\frac{\frac{\delta Y}{\delta H}}{\frac{\delta Y}{\delta L}}\right) = \frac{\sigma-1}{\sigma}\ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\ln\left(\frac{H}{L}\right). \tag{3}$$

Equation 3 shows that relative wages are determined by three factors – the degree of substitutability between skill groups σ, the relative supply of high-skilled workers $\frac{H}{L}$, and the skill bias of technology $\frac{A_H}{A_L}$. As we approach the perfect substitutes case ($\sigma \rightarrow \infty$), only skill bias matters. As we approach the perfect complements case ($\sigma \rightarrow 0$), only skill supplies matter. In reasonable intermediate cases, the skill premium depends on the interaction between relative demand and relative supply.[4] An increase in H relative to L lowers the wages of high skilled workers because the labor demand curve is downward sloping. Conceptually, H is being used more intensively but less productively, perhaps because high-skilled workers are shifting into occupations and tasks that were previously performed by low-skilled workers.

Equation 3 shows that, all else equal, growth in the relative supply of high-skilled workers always reduces the skill premium. This in turn implies that the enormous increases in global educational attainment over the last seventy years should have caused the college wage premium to decline. Yet if anything, the opposite has occurred. The explanation offered by the canonical model is that the relative demand, or the skill bias of technology $\frac{A_H}{A_L}$, must have increased at least as fast as the supply of skills. Growth in the college wage premium suggests that the demand for skills is "racing" ahead of supply (Goldin and Katz, 2008).

Empirical tests of the canonical model use data on relative skill supplies ($\frac{H}{L}$) and relative wages ω and leave the elasticity of substitution σ and the skill bias of technological change ($\frac{A_H}{A_L}$) as parameters to be calibrated or estimated. Katz and Murphy (1992) estimate the canonical model using data from the U.S. Current Population Survey (CPS) between 1963 and 1987. They assume that skill bias follows a linear trend, which allows them to directly estimate σ. They find an elasticity of substitution of roughly 1.4, and show that the model is capable of explaining both the declining wage premium for college educated workers in the 1970s and its rapid rise in the early 1980s. Goldin and Katz (2007) estimate a version of the canonical model using U.S. data back to 1915, and Autor et al. (2020) estimate it using data for more recent years. With some exceptions, the canonical model provides a surprisingly good fit to more than a century of U.S. data.[5]

The canonical model also explains trends in wage inequality in other developed countries. Austria, Belgium, Canada, Denmark, Finland, France, Germany, Luxembourg, Japan, Norway, Sweden, and the United Kingdom all experienced increasing educational attainment and a growing college wage premium in the 1980s and 1990s (Betts, 1997; Berman et al., 1998; Machin and Van Reenen, 1998;

[4]More formally we can derive the demand curve for skills as $\frac{\delta \ln \omega}{\delta \ln(\frac{H}{L})} = -\frac{1}{\sigma}$.

[5]Goldin and Katz (2007) note that the model performs poorly in the 1940s and 1970s and attribute this to institutional factors like wage-setting policies and unions, and refer to it humbly as the "supply-demand-institutions" (SDI) framework. Acemoglu and Autor (2011) and Autor (2017) estimate higher elasticities of substitution for more recent years of data, which suggests that the skill premium has grown more slowly in recent years than the original Katz and Murphy (1992) would have predicted. Deming (2023a) discusses several possible reasons for this empirical pattern, including boom-bust technology cycles, declining college quality, and a higher long-run substitution elasticity (Beaudry et al., 2016; Carneiro et al., 2011; Bils et al., 2022).

Gosling et al., 2000; Dustmann et al., 2009). Moreover, several studies provide micro evidence that computerization and related technological developments increased relative wages for college-educated workers, thereby providing empirical support for the idea that technological change has been skill-biased (Akerman et al., 2015; Lindner et al., 2022).

2.3 Human capital and economic development

The canonical framework in the study of economic growth is the Solow-Swan model, which posits a Cobb-Douglas aggregate production function for a composite final good and that takes capital and labor as inputs (Solow, 1956):

$$Y_c = K_c^{\alpha}(A_c H_c)^{1-\alpha}. \tag{4}$$

where Y_c represents aggregate output, K is capital and α is the capital share, H is quality-adjusted labor, and A is a technology term, often called total factor productivity (TFP). Following Hall and Jones (1999) we can rewrite the equation above in terms of log output per worker:

$$ln\left(\frac{Y_c}{L_c}\right) = \frac{\alpha}{1-\alpha} ln\left(\frac{K_c}{Y_c}\right) + ln\left(\frac{H_c}{L_c}\right) + ln\left(\frac{A_c}{L_c}\right) \tag{5}$$

which can be estimated with cross-country data on incomes and factor shares. Human capital per worker $\frac{H_c}{L_c}$ is measured using years of schooling or other data on educational attainment. While data on H, K, and L are widely available, measurement of TFP is much more difficult, and thus $\ln(\frac{A_c}{L_c})$ is often called the "Solow residual" because it is the variation not explained by other variables. Mankiw et al. (1992) estimate a version that replaces the standard L for labor with a quality adjustment for human capital differences as proxied by school enrollment rates. Their augmented Solow-Swan model shows that countries with higher rates of human capital grow faster, and that human capital is positively related to GDP growth over a 25-year period.

A key limitation of cross-country regressions is that differences in school enrollment probably covary with other determinants of growth such as technology adoption, institutions, and other factors (Klenow and Rodriguez-Clare, 1997). In other words, just as in the Mincer model, schooling is endogenous. An alternative approach is development accounting, which asks how much of the cross-country variation in income can be statistically explained by human capital. With development accounting, the burden is on the data – any income differences that are not explained by schooling are attributed to TFP through the "Solow residual". Caselli (2005) finds that physical and human capital explain only about 30 percent of the cross-country variation in income, leaving the other 70 percent to the Solow residual.

Development accounting estimates of the importance of human capital depend greatly on measurement and on the assumed structure of the aggregate production function (Rossi, 2020; Hendricks and Schoellman, 2023). On the measurement side, Hanushek and Woessmann (2012) incorporate international tests of numeracy and literacy into a development accounting framework and find that achievement measures are positively related to growth above and beyond schooling attainment. Several studies find that labor market returns to experience are substantially higher in more developed countries and in recent years, and argue that this likely reflects differences in human capital accumulation on the job (Lagakos et al., 2018; Deming, 2021; Jedwab et al., 2023).

Most development accounting exercises assume that workers with different levels of human capital are perfect substitutes, which allows them to equate marginal products with wages and "add up" a country's human capital stock using aggregate data (Klenow and Rodriguez-Clare, 1997; Bils and Klenow, 2000). This contradicts the predictions from and evidence supporting the canonical model. Jones (2014) estimates versions of the canonical model across countries with values of the elasticity of substitution σ from the literature and finds that allowing for such substitutability increases the explanatory power of human capital enough to account for 100 percent of cross-country income differences. In a reply, Caselli and Ciccone (2019) argue that the contribution of human capital may be even less than it appears since it is often correlated with better technology and stronger institutions. The ideal way to make progress on these questions is some kind of natural experiment that asks how wages change with the human capital stock or TFP of a country, holding all other factors constant.

Hendricks and Schoellman (2018) provide important quasi-experimental evidence on this question by studying the wage gains from migration. Assuming that human capital travels with individuals who migrate, changes in their relative wages across countries with different technologies and institutions tell us something about the importance of human capital for explaining cross-country income differences. Using data on pre- and post-migration wages from the New Immigrant Survey (NIS), they find that migrants to the U.S. experience wage gains that are equivalent to 38 percent of the gap in GDP-per-worker from each source country. This implies that the remaining 62 percent is explained by human capital.[6] A development accounting framework that is calibrated using the wage gains from migration suggests that human capital accounts for between 50 and 75 percent of cross-country income differences (Hendricks and Schoellman, 2023).

[6]One might be concerned that human capital does not fully transfer across countries. Hendricks and Schoellman (2018) find that human capital accounts for at least half of cross-country income differences even among immigrants who work in the same occupations and come to the U.S. with a job in hand. They also argue that their estimates are a lower bound if immigrants are self-selected on earnings *gains*.

2.4 The task framework

Despite the amazing success of the canonical model in explaining the wage structure within and across countries, it has some key limitations. The first is that technology never replaces work or creates new work, but rather enters the model only by augmenting labor (e.g. through the A_H and A_L terms). This defies the conventional wisdom and the empirical evidence that new technologies automate tasks previously performed by people (Acemoglu and Restrepo, 2018). Second, it is hard to generate non-monotone changes in the wage structure with only two skill groups, so the canonical model cannot easily explain job polarization (Autor et al., 2008). Third, the assignment of workers to jobs is implicit. Would low- and high-skilled workers have different earnings in the same occupations? How does an increase in the relative supply of college-educated workers change the assignment of workers to jobs and tasks? To make progress, we need a model that considers tasks rather than workers as the fundamental unit of work output.

Acemoglu and Autor (2011) develop a task-based framework to address the shortcomings of the canonical model. Their model takes tasks as the main inputs in the aggregate production function, with a lower-level production function where labor is supplied to each task. Acemoglu and Autor (2011) develop the model with low-, middle-, and high-skilled workers (L, M, and H) although it is flexible enough to accommodate more or fewer skill groups. They assume that job tasks can be arrayed on a single dimension of "complexity" and that high-skilled workers are relatively more productive in the most complex tasks, followed by medium-skilled and low-skilled workers. This simple structure of comparative advantage generates an equilibrium defined by two endogenous task thresholds (the boundaries between L and M, and between M and H) that define relative wages and shift in response to changes in skill supply and demand.

The Acemoglu and Autor (2011) task framework nests the canonical model as a special case, while adding much more flexibility. The two models are identical in the case where there are only two tasks and low- and high-skilled workers each have a comparative advantage in one of them. Moreover, the two models generate the same empirical predictions when the task framework has only two skill groups. In both models, relative wages depend on the skill bias of technological change and on relative skill supplies. However, in the task framework, relative wage changes correspond to changes in the assignment of worker skill groups to tasks, which we can think of as occupational sorting.

A large literature in economics documents employment polarization in the U.S. and other OECD countries, with growth in both low- and high-skilled occupations relative to middle-skilled occupations (Autor et al., 2008; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014). Polarization has been linked to the declining price of computer capital, which directly replaced workers in "routine" tasks that were disproportionately performed by middle-skilled workers (Autor et al., 2003). The task framework accommodates this naturally by modeling computerization as giving machines comparative advantage over middle-skilled workers in some tasks. This reduces the average complexity of tasks performed by type M workers, lowering their relative wages. Consistent with the theory, workers with high school degrees or some college education have shifted out of clerical and administrative positions and into lower-paying service sector jobs (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Beaudry et al., 2016).

Acemoglu and Restrepo (2018) modify the task framework further, showing that the adoption of robots and specialized software in the United States reduced employment and wages for workers in industries most exposed to these new automation technologies. Acemoglu and Restrepo (2022) aim to understand the potential implications of automation technologies on the broader wage structure – beyond those experienced by workers in routine jobs replaced by technology. They estimate that the labor market penetration of automation technologies can explain between 50 and 70 percent of changes in the United States wage structure between 1980 and 2016. Autor et al. (2022) study the impact of automation but also "new work" using data on new job titles linked to patent applications. They find that new technologies since 1980 have been concentrated in personal services and in well-educated and highly-paid professional occupations, which helps explain the origins of polarization.

Although the task framework adds flexibility and a closer mapping between theory and data, it does not have much to say directly about human capital. For example, Acemoglu and Autor (2011) explain polarization by assuming that "middle skill" tasks are routine and thus replaceable by technology. Similarly, Acemoglu and Restrepo (2018) assume that only routine tasks can be automated and that the impact of education operates only through the routineness of a worker's industry and occupation. Neither approach explains why routine tasks are best suited to workers with some education but not too much (e.g. "middle skill"), or why educated workers sort into non-routine jobs when new technologies are adopted.

3 Human capital investment

3.1 Life-cycle models of human capital investment

If human capital is an investment that pays off, what is the optimal investment portfolio at each stage of the life-cycle? Empirically, schooling attendance is concentrated early in life and tends to be full-time. Labor earnings increase rapidly early in life and then level off. The seminal model of Ben-Porath (1967) explains these empirical regularities parsimoniously. We develop a very basic version of the Ben-Porath model here to guide the discussion.

In Ben-Porath (1967), workers maximize the present discounted value of lifetime earnings by allocating their time between human capital investment and work. Time at work increases earnings, but time spent investing increases future earnings potential. Workers solve an intertemporal optimization problem:

$$max_s \sum_{t=1}^{T} B^{t-1} w_t (1 - s_t) \tag{6}$$

where t indexes years, w_t is the wage, and B is a discount factor. Workers retire exogenously at $t = T$ and allocate a unit of time each year between schooling investment and market work, so that $s_t + l_t = 1$ and $0 \leq s_t \leq 1$ and $0 \leq l_t \leq 1$. Each period, workers earn $h_t l_t$, their competitive market wage (e.g. their human capital) times the amount of time spent working. The human capital production function is:

$$h_{t+1} = h_t + \alpha(s_t h_t)^{\theta} \tag{7}$$

Human capital tomorrow depends on the current stock of human capital, time spent investing (s_t), and the parameters $\alpha > 0$ and $\theta > 0$. The scale parameter α indexes the efficiency of time spent learning, and is often used to represent the worker's cognitive ability (Neal and Rosen, 2000; Huggett et al., 2006; Deming, 2023b). The share parameter θ represents the output elasticity, or returns to scale, in human capital investment. Since human capital tomorrow depends on today's human capital, an implication of this model is that human capital is self-productive (Heckman, 1976; Rosen, 1976).

This simple version of the Ben-Porath model can be solved as a dynamic programming problem for different values of α and θ (Heckman et al., 1998; Sanders and Taber, 2012).[7] The model endogenously generates an early life period where $s_t = 1$, which Ben-Porath (1967) interprets as schooling. Wage growth starts off fast but slows down because of the concavity of the human capital production function. Earnings grow faster than wages because workers optimally spend more time working and less time investing as they age. As α increases, workers spend more time in school, earn higher peak wages, and have a steeper age-earnings profile. The same is generally true of θ, although θ has a bigger impact on the optimal amount of time spent in full-time schooling.

Sanders and Taber (2012) extend the Ben-Porath model to allow human capital to be a multidimensional vector, with different weights over industries, occupations or firms as in Lazear (2009). In their model, workers match to firms based on their initial human capital and then move across firms based on search frictions. They identify distinct strategies where workers either invest in general skills and search intensively, or they invest in firm-specific skills and plan to stay. This is an interesting avenue for future research.

Adda and Dustmann (2023) integrates multi-dimensional skills into the Ben-Porath model. In their model, workers either accumulate routine/manual skills or cognitive/abstract skills. While routine/manual skills are important sources of wage growth early in workers' careers, the value of

[7]Versions of the Ben-Porath (1967) model sometimes add consumption of market goods, a leisure decision, a human capital depreciation term, and other wrinkles (Neal and Rosen, 2000; Blandin, 2018)

cognitive/abstract skills increases over the life-cycle as they allow workers to transition to occupations relying on abstract skills.

In the Ben-Porath model, learning and earning are substitutes. An alternative approach is the learning-by-doing (LBD) model, where market time directly increases human capital. Blandin (2018) contrasts the empirical predictions of both models and generalizes the model to allow for schooling and production time to both contribute to human capital development. Manuelli and Seshadri (2014) use cross-country income and schooling data to nest the Ben-Porath model into a development accounting framework. Their model provides a good fit to data on educational attainment and age-earnings profiles, and they find an important role for school quality in explaining cross-country income differences.

3.2 The technology of skill formation

In the Ben-Porath model, individuals spend more time learning early in life because they have a longer horizon over which to recoup their human capital investment. In a series of papers, James Heckman and several co-authors argue that early life investment is optimal for technological reasons. They illustrate this concept with what has become known as the "Heckman Curve", a figure showing a declining rate of return with age to investment in human capital and a horizontal break-even line that intersects somewhere during primary school age. The assertion is that the rate of return to human capital investment when a person is young is higher than when that same person is older, and that there is no equity-efficiency tradeoff for very young children (Carneiro and Heckman, 2003; Heckman et al., 2006a).

Cunha and Heckman (2007) formalize these ideas with a model of life-cycle skill formation. Individuals are born with human capital h (which could reflect IQ, parental education, income, and other fixed factors) and an initial endowment of skills. To build intuition, we focus on a simple model with only two periods of childhood investment producing a stock of adult skills ($A_T = A_3$). Consider a CES human capital production function:

$$A_3 = h[\gamma I_1^{\phi} + (1-\gamma) I_2^{\phi}]^{1/\phi} \tag{8}$$

with $0 \leq \gamma \leq 1$ as a share parameter reflecting the relative importance of early vs. late childhood investments. Higher values of γ magnify the importance of "self-productivity", where early childhood investment I_1 increases the late childhood stock of skills A_2, and in turn increase the productivity of late childhood investments I_2. Self-productivity is captured by the simple and memorable phrase "skills beget skills" (Cunha and Heckman 2007). Intuitively, self-productivity matters for cumulative learning processes such as mathematics, where concepts build upon one another.

The elasticity of substitution $\frac{1}{1-\phi}$ for $\phi \leq 1$ measures the exchangeability of early and late skill investments. As ϕ decreases, balanced investment strategies have higher returns, a phenomenon referred to by Cunha and Heckman (2007) as *dynamic complementarity*. Dynamic complementarity occurs when skills acquired in period $t-1$ increase the productivity of period t investment. The reverse is also true – low levels of investment early in life make it harder to remediate early disadvantage. In the limiting case where $\phi \to \infty$, the equation above converges to a perfect complements production function $h[min(I_1, I_2)]$. Early and late investments are perfect substitutes when $\phi = 1$.

The Cunha-Heckman model also allows for multiple skills, each with different technology parameters. There is evidence that cognitive skills are only malleable early in life, whereas "non-cognitive" skill deficits may be easier to remediate (Cunha and Heckman, 2007, 2010). Cross-productivity effects are also possible, where the stock of one type of skill affects the productivity of investment in other skills. For example, developing self-control early in life might increase the return on investment later if students are more able to sit through increases in instructional time or longer school days.

Cunha and Heckman (2007) derive the optimal ratio of early to late investment in human capital:

$$\frac{I_1}{I_2} = \left[\frac{\gamma}{(1-\gamma)(1+r)} \right]^{\frac{1}{1-\phi}} \tag{9}$$

where r is the interest rate. Higher values of γ suggest that early investments are more productive. Lower values of ϕ suggest that early investments should be supplemented in later periods because of dynamic complementarity. The combination of high γ and low ϕ implies that later investments are not very productive and that they cannot easily make up for early childhood skill deficits. This rationalizes the "Heckman Curve".

3.3 Empirical evidence on the technology of skill formation

There is strong evidence for the economic value of skill investments in early childhood (e.g. Heckman and Masterov, 2007; Duncan and Magnuson, 2013; Almond et al., 2018).[8] Two randomized evaluations of small-scale, intensive preschool interventions - The High/Scope Perry Preschool Project and the Carolina Abecedarian Project – find large and long-lasting impacts of early education on earnings, educational attainment, crime, and other adult outcomes (Schweinhart et al., 2005; Heckman et al., 2013; Campbell et al., 2014; García et al., 2020). Several studies of large-scale public preschool programs find long-run impacts educational attainment, earnings, and health (Garces et al., 2002; Ludwig and Miller, 2007; Deming, 2009; Bailey et al., 2020; Gray-Lobe et al., 2023).

Further support for the importance of early human capital investment comes from the "fetal origins" literature, which finds large long-run impacts of *in utero* and fetal health, maternal stress and

[8] See also recent papers which highlight the role of parental investments in early childhood (Agostinelli and Wiswall, 2016; Attanasio et al., 2020; Caucutt and Lochner, 2020).

substance use, and adverse early life events such as exposure to pollution and disease (e.g. Almond et al., 2018). In many cases, mild shocks for adults such as increased exposure to seasonal flu or periodic fasting during Ramadan have large impacts on the adult outcomes of exposed children *in utero*, which suggests increased sensitivity to early life investments (Almond and Currie, 2011).

A small number of studies directly test for dynamic complementarity in the Cunha-Heckman framework and find mixed results.[9] Cunha and Heckman (2010) estimate a structural model of the technology of skill formation using panel data on parental investments and child and young adult outcomes and find evidence for dynamic complementarity in cognitive skill investments. Johnson and Jackson (2019) find larger benefits of Head Start for children attending better-funded schools, while Mbiti et al. (2019) find that cash grants to schools are more effective when also paired with teacher performance incentives. However, Rossin-Slater and Wüst (2020) find that the benefits of early childcare were larger for children who had not been exposed to a nurse home-visiting program, which suggests dynamic *substitution* between human capital investments. Malamud et al. (2016) find no evidence of interactions between better home and school environments, possibly because of compensatory responses by parents. Carneiro et al. (2022a) find no evidence of dynamic complementarity between classroom grade levels in schools in Ecuador.

There are many examples in the literature of high returns to early life interventions. This does not imply, however, that returns are lower for interventions later in life. In fact, the evidence suggests that there are high returns to human capital investments through childhood and young adulthood. Hendren and Sprung-Keyser (2020) analyze 133 experimental and quasi-experimental policy interventions in the United States using a unified welfare analysis framework. They calculate the "marginal value of public funds" (MVPF) for each of these studies as the ratio of recipients' willingness to pay by the net cost to the government. An MVPF greater than one translate into a welfare improvement relative to a non-distortionary cash transfer. An infinite MVPF means that the program is a Pareto improvement that "pays for itself", typically because of the positive fiscal externality generated by large treatment effects on earnings which pay back program costs through increased tax revenue.

Hendren and Sprung-Keyser (2020) find that investments throughout childhood have high MVPFs, and often pay for themselves. The early childhood interventions cited above have very high MVPFs, but so do other policies such as increased K-12 school spending, financial aid for low-income college students, and sectoral employment programs for young adults. This finding is not driven by particular features of their welfare analysis framework, and the studies they cite also have high returns when measured with more conventional approaches such as benefit-cost ratios (Rea and Burton, 2020).

A handful of papers also study the effects of otherwise similar childhood shocks that are experi-

[9] There is also some evidence on the cross-productivity in human capital development. For example, Hanushek et al. (2022) show that patience is related to further investments in human capital while risk-taking can reduce investments in human capital.

enced at different ages. Chetty et al. (2018) find that the impact of moving to a better neighborhood is roughly linear in years of exposure. In contrast, Deutscher (2020) finds that the effects of neighborhoods are most important in teenage years. Further, a study based on the randomized allocation of military families to different neighborhoods finds that location in high school is twice as important as that in elementary school for earnings and college outcomes (Kawano et al., 2024). Likewise, Lenard and Silliman (2024) find larger effects of peers later in childhood, and Carneiro et al. (2022b) finds greater impacts of parental job loss for teenagers compared to younger children. Further, Bastian and Michelmore (2018) study the EITC and find that additional family resources between ages 13-18 improve childrens' later life outcomes, while their estimates show little evidence of effects at earlier ages.

In sum, human capital investments are roughly equally productive between the ages of 0 and 25. That does not necessarily invalidate the Cunha and Heckman (2007) theory, which is about technological possibilities rather than practical realities. For example, even very young children may already be on the flat of the Heckman Curve. Exposure to disease, pollution, and other adverse events have temporary impacts on adults and young children but long-lasting and permanent impacts on fetuses (Almond et al., 2018). Sensitivity to early investments might be most important before a child is born, with the difference between early and late childhood being less important. More broadly, the real world is messy, and it may be that few people reach their full potential due to lack of opportunity, credit constraints, and other barriers. If almost everyone is inside their own skill frontier, the Heckman curve may not apply in practice even if it exists in principle.

What about human capital investments in adulthood? The empirical evidence on job training is mixed, with many programs delivering disappointingly small impacts (Heckman et al., 1999). On the other hand, wages grow rapidly over the life-cycle, and this may partly reflect high returns to on-the-job learning (Heckman et al., 1998; Sanders and Taber, 2012; Deming, 2023b). Using administrative data from Brazil and Italy, Arellano-Bover and Saltiel (2024) show that wages grow much faster in some firms than in others. Using a life-cycle search model to study patterns of firm-specific wage-growth in Germany, Gregory (2020) estimates that firm investments in on-the-job learning explain 40 percent of the increase in earnings inequality across adulthood.

Differences in returns to work experience may also be important in explaining productivity differences between countries (Lucas Jr, 1988; Rossi, 2020). Using data from more than a thousand household surveys in 145 countries, Jedwab et al. (2023) document an average return to experience of about 2 percent – about a quarter of the returns to each year of education in their sample. While the returns to education are relatively consistent across national contexts, they find that the returns to experience are considerably larger – more than 3 percent – in developed economies. Plugged into a growth accounting framework, they estimate that differences in the contribution of work experience are roughly as important as formal education in explaining differences in productivity growth across countries. Similarly, Ma et al. (2024) show that firm investments in job training explain about 70 percent of differences in worker wage growth in a sample of over a 100 countries.

A key outstanding question is the extent to which wage growth and on-the-job learning should be thought of as general or specific human capital. An important conceptual paper in this literature is Lazear (2009), who argues for a "skill weights" approach where all skills are general but firms can demand them in scarce combinations. Other issues deserving more attention include the relationship between human capital and technology, including whether earlier "vintage" skills eventually become obsolete (Chari and Hopenhayn, 1991; Kredler, 2014). Krueger and Kumar (2004) argue that economies where workers possess a higher degree of general – rather than vocation-specific – training will be better equipped to adapt to changes in the labor market. Deming and Noray (2020) consider a simple model where earnings growth is a race between gains from on-the-job learning and losses from skill obsolescence. They find that the earnings premium for technology-intensive majors like computer science and engineering is initially very high but declines rapidly, consistent with skill obsolescence. They also show directly using job vacancy data that skill demands change faster in technology-intensive occupations.

4 Multidimensional human capital

4.1 Micro evidence from education and labor market interventions

Many studies have found a strong correlation between cognitive test scores and earnings as well as other positive life outcomes (Heckman et al., 2006a; Chetty et al., 2011). Moreover, there is a great deal of evidence that human capital interventions increase earnings directly through their impacts on academic achievement. For example, Chetty et al. (2014) find that students who are assigned to a teacher with high test score value-added have higher adult earnings.

Most of these studies evaluate educational interventions as a package. However, in a particular clever study, Carlsson et al. (2015) isolate the impact of time in school on test scores by exploiting variation in the age and school grade at which Swedish men must take a military enlistment exam. They find that test scores increase by one percent of a standard deviation for every ten days in school, which translates to an impact of schooling of about 0.2 standard deviations per year. Importantly, this impact holds for crystallized (knowledge-based) intelligence tests but not fluid intelligence assessments like logic and spatial reasoning. Cascio and Lewis (2006) find a similar result in a smaller U.S.-based sample.

Education has a large causal impact on earnings and later life outcomes, and much of this impact is mediated through achievement gains. However, the long-run impacts of educational interventions are sometimes much larger than what would be predicted by achievement gains alone.

Studies have increasingly found that skills like patience, self-control, adaptability, conscientiousness, and teamwork are important predictors of later life success. The intellectual origins of this work derive from studies of Perry Preschool and other early childhood programs by James Heckman and coauthors, who call these capacities "non-cognitive" skills because they are not captured by test scores. They found that these interventions improved adult outcomes without affecting measured IQ (Nores et al., 2005; Heckman et al., 2010a,b). Heckman et al. (2006b) interpret this as evidence of "non-cognitive" skills being the driving force behind the longer-term impacts of the program. Deming (2009) found that Head Start, a national public pre-K program for poor children, improved long-run outcomes despite "fade out" of test score gains, and Gray-Lobe et al. (2023) found similar results in a recent study of public pre-K in Boston. A common explanation for the persistent returns to early childhood education is that they are driven by improvements in non-cognitive rather than cognitive skills (e.g. Heckman et al., 2013; Bailey et al., 2020; Li et al., 2020).

The studies cited above mostly establish that test scores alone are insufficient to judge the short-run success of educational interventions. They do not, however, directly measure skills beyond test scores (thus the definition by negation, "non-cognitive"). Heckman et al. (2006a) was one of the earliest studies to define what is meant by "non-cognitive" skills and to measure them empirically. Using data from the National Longitudinal Survey of Youth 1979 cohort (NLSY79), Heckman et al. (2006a) find that latent indices of cognitive and non-cognitive skills have independent and somewhat different predictive power for a wide variety of adult outcomes. Their measures of cognitive skills are based on different components of the Armed Forces Qualifying Test (AFQT), a fairly standard achievement test. Their measures of non-cognitive skills are the Rotter Locus of Control and the Rosenberg Self-Esteem Scales, which ask the degree of control individuals feel over their lives and their perceived self-worth respectively. Notably, Heckman et al. (2006a) find that variation in these non-cognitive skill measures predicts earnings and risky behavior about as much as variation in test scores.

Chetty et al. (2011) find that the quality of a randomly assigned kindergarten classroom increased test scores and long-run earnings, even though the initial achievement gains “faded out” after a few years. Despite test score "fade out", they show that impacts persist on teacher reports of classroom effort and attitude taken in 4th and 8th grade, and that more of the long-run impact on adult earnings was statistically explained by increases in “non-cognitive” skills than by initial achievement gains. Jackson et al. (2020) find that high schools with high “value-added” in promoting hard work and social well-being increase students’ high school graduation and college attendance, even after accounting for their impact on academic achievement. Moreover, teachers have sizeable impacts on behaviors like absences and suspensions, and their effectiveness in reducing these harmful behaviors strongly predicts long-run impacts on high school graduation and college attendance (Jackson, 2018; Petek and Pope, 2023).

Can skills like teamwork, patience, and grit be developed? Some promising recent studies suggest that the answer is yes. Alan and Ertac (2018) study a program that encourages patience and forward-looking behavior in primary schools in Turkey, and find that it increase grades and classroom behavior three years later. Alan et al. (2019) find similar long-run effects of an intervention to increase "grit" (persisting in an effortful, unpleasant task - see Duckworth (2016) for a review). Algan et al. (2022) find that a program for young boys in Montreal that sought to improve self-control and social skills increased educational attainment, reduced crime, and increased annual income by about 20 percent. Several programs targeting childrens' socio-emotional skills find increases in grades and educational attainment and reductions in learning disability diagnosis (Sorrenti et al., 2024; Kosse et al., 2020; Schunk et al., 2022; Barbosa, 2023; Carlana and La Ferrara, 2024). Brown et al. (2022) randomly assign a group of 1,600 Indian primary school students to two types of effortful cognitive activity—one that is clearly academic, and one that is not. Both interventions increase the ability to concentrate and both lead to increased academic performance, suggesting that what they call "cognitive endurance" improves with practice.

Turning to the labor market, Adhvaryu et al. (2023) find that on-the-job "soft skills" training increased the productivity of garment factory workers in India by 13.5 percent, with larger impacts when work is more team-intensive. A social skills training program improved entrepreneurial performance in Togo (Dimitriadis and Koning, 2020), and a three-week "soft skills" program for high school students in Uganda improved earnings more than when the program focused on "hard" skills (Chioda et al., 2021).

In an educational setting in Zambia, Ashraf et al. (2020) find that a training program in negotiation skills for adolescent girls improved educational outcomes. Mehmood et al. (2024) study a program that provided junior ministers in Pakistan with training to improve altruisim, and found that the program improved measures of teamwork and soft skills. Dube et al. (2023) study the effects of an intervention focused on improving the decision-making processes of police officers and find that the program reduced the use of force, discretionary arrests, and injury in the field while maintaining other measures of performance at prior levels. Allemand et al. (2023) find that a program in Senegal targeting conscientiousness improves earnings and rates of employment. Several other papers document effects of training programs targeting soft skills on labor market outcomes, though many of these are unable to pinpoint exactly which skills drive the effects on later outcomes (Groh et al., 2016; Acevedo et al., 2020; Osman and Speer, 2022; Barrera-Osorio et al., 2023; Brudevold-Newman and Ubfal, 2023). We need more research across varying programs and contexts to build an economic theory of how and why skills like those required for teamwork matter.

Overall, there is strong evidence that off-the-shelf measures of personality and mindset are strong predictors of adult labor market success and can be improved through interventions - see Borghans et al. (2008), Kautz et al. (2014), and Deming (2022) for further detail.

4.2 Macro evidence

Several studies estimate economic returns to various "non-cognitive" skills in ways that facilitate comparison to test score impacts. These studies typically find that the impact of a given increase in non-cognitive factors is similar or larger in size to test score impacts, although it is unclear how to interpret the results given differences in scaling and interpretation.

Lindqvist and Vestman (2011) use Swedish military enlistment data to estimate labor market returns to cognitive and non-cognitive skills, where the latter is measured as traits like emotional stability and persistence from a personal interview administered by a trained psychologist. They find impacts of similar magnitude overall for both types of skills, although noncognitive skill appears to be more important at the lower end of the earnings distribution and is driven by employment rather than wages. Using the same data source but for more recent years, Edin et al. (2022) show that the wage return to noncognitive skill nearly doubled between 1992 and 2013, and has been larger than the return to cognitive ability since the early 2000s.[10] Moreover, they find that the return to noncognitive skills is twice as large as the return to cognitive skills when using earnings rather than wages (which includes the impact of skills on employment). Also using Swedish enlistment data, Hermo et al. (2022) document an increase in the labor market value of logical reasoning skills (e.g. fluid intelligence) compared to vocabulary knowledge (e.g. crystallized intelligence), and they argue that this increase in relative demand for skills led to changes in skill supply across cohorts. Suggesting a broad range of non-cognitive skills may be malleable, Jokela et al. (2017) find that average values of economically valuable personality traits like sociability and self-confidence have risen in Finland between the 1962 and 1978 birth cohorts.

The rising return to non-cognitive skills holds in other countries as well. Izadi and Tuhkuri (2024) use military enlistment data from more than half a million Finnish men from 2001 to 2015 to studying trends over time in the labor market returns to skills. They find that the earnings return to non-cognitive skills increased by about 30 percent in Finland between 2001 and 2015, while the return to cognitive skills *decreased* by 35 percent. Interestingly, they show constant returns over time to conscientiousness, whereas the return to extraversion has increased by 75 percent. The impact of extraversion on employment increased a lot in Finland over this period, although the impact of extraversion on earnings among those who are full-time employed also increased substantially.[11] In a companion paper, Izadi and Tuhkuri (2021) find that among workers who suffer a mass layoff, cognitive skill and extraversion are associated with smaller earnings losses and faster reemployment in the same occupation and industry. Aghion et al. (2024) find that social skills are

[10] They also show that selection into education based on skills did not change over this period, and that the increasing return to non-cognitive skills holds similarly at various wage quantiles.

[11] Just as in Edin et al. (2022), changing selection into education does not drive the results and the impact of extraversion is increasing at all wage quantiles.

important predictors of wage growth for low-skilled workers in the United Kingdom.

Using data from successive NLSY cohorts entering the labor market in the 1980s compared to the 2000s, Deming (2017) finds that the economic return to social skills in the United States more than doubled, and that jobs requiring high levels of social interaction grew by nearly 12 percentage points as a share of the US labor force. In an earlier paper with the same data, Castex and Kogan Dechter (2014) show that the return to cognitive skills in the U.S. has declined, even as the college wage premium increased. Attanasio et al. (2021) find growing inequality over time in socio-emotional skills in the U.K. Reyes (2023) uses the random order of question items on college admissions exams in Brazil to decompose performance into cognitive endurance and true, fatigue-adjusted ability. He finds that a one standard deviation in cognitive endurance increases earnings by 5.4 percent, which is about one-third the size of the impact of fatigue-adjusted ability.

Overall, there is a surprising amount of recent evidence that non-cognitive skills matter greatly in the labor market, perhaps as much or more than cognitive skills. Moreover, the returns to these skills appear to be growing over time, both in absolute and relative terms. However, what is missing is a broader understanding of what "non-cognitive" or "soft" skills are, and how to measure and develop them. For that we need a broader conceptual framework to understand how different kinds of skills fit together to determine a person's human capital and earnings potential.

4.3 Higher-order skills

Deming (2022) argues that the appropriate term for the capacities measured in many prior studies is "higher order" skills. This follows from an old and highly influential pedagogical resource called the *Taxonomy of Educational Objectives*. In 1956 a committee of educators led by Benajmin Bloom developed what has become known as Bloom's Taxonomy (Bloom et al., 1956). Bloom's taxonomy establishes a hierarchy of cognitive processes in learning, with routine cognitive activities at the base of a pyramid and higher-order cognitive processes as you move up to the top. The layers of the pyramid (from bottom to top) are knowledge, comprehension, application, analysis, synthesis, and evaluation. The taxonomy was updated from noun to verb form and revised slightly in 2001, so that the modern ordering is remember, understand, apply, analyze, evaluate, and create.

School achievement exams, and even tests like the SAT or the Armed Forces Qualification Test (AFQT), stay mostly at the bottom two layers of the pyramid, asking respondents to recall facts, understand concepts, recognize patterns, and classify information. As the pyramid structure implies, these foundational skills are required for developing higher-order skills like applying knowledge to solve new problems, connecting one's own ideas and skills to others, and designing and creating novel concepts.

Are higher-order skills conceptually distinct from traditional measures of cognitive skills? An annual survey administered by the National Association of Colleges and Employers (NACE) routinely finds that U.S. employers cite teamwork skills and the ability to solve problems as the two most important and hard-to-find qualities in new hires (NACE, 2024). Deming and Kahn (2018) find growing demand for social skills based on online job vacancies in the U.S., and Deming (2021) shows that the share of jobs requiring decision-making more than tripled between 1980 and 2018.

Higher-order skills are clearly important, but it is challenging to measure them well using existing data (Humphries and Kosse, 2017; Almås et al., 2023). Most studies have used self-reported answers on Likert scale questionnaires (1 to 5 or 1 to 7, ranging from "strongly disagree" to "strongly agree"). These scales do not have any cardinal meaning, and as a result their predictive power for later life outcomes varies widely across contexts. For example, West et al. (2016) find that high-performing charter schools increase student achievement but decreased self-reported conscientiousness and grit, probably because of changes in the peer comparison group and teacher expectations. Another issue is that personality traits can be helpful in some contexts and harmful in others. Conscientiousness is associated with higher average educational attainment and earnings, but conscientious people are less likely to be successful as entrepreneurs, perhaps because they are rule followers (Levine and Rubinstein, 2017; Papageorge et al., 2019).

One way to make progress on defining and measuring higher-order skills is to design performance-based measures of skills that are connected to a theory about why they matter and in what contexts. Weidmann and Deming (2021) develop an experimental method for identifying individual contributions to group performance. They randomly assign individuals to multiple teams and estimate each individual's "team player" effect as their regression-adjusted impact over multiple groups. Individuals who consistently improve their team's performance are "team players". They find strong evidence of individual variation in team contribution, and that team players score higher on a widely-used measure of emotional perceptiveness called the "Reading the Mind in the Eyes" test (RMET) (Baron-Cohen et al., 2001). In contrast, the team player effect is not associated with IQ or personality traits like conscientiousness or extraversion. Extraversion measures *sociability*, or preferences for social interaction. This is not the same thing as the *skill* of increasing team performance.

The experiment in Weidmann and Deming (2021) demonstrates a direct relationship between social skills, teamwork, and individual productivity. Arcidiacono et al. (2017) estimate a non-experimental version of Weidmann and Deming (2021) using professional basketball lineups and find strong evidence of productivity spillovers across teammates that are not fully priced by the market. Bonhomme (2021) develops an econometric framework to estimate team player effects using non-experimental data. Much more work is needed to understand team production in the labor market and the impact of social skills on team performance.

Another important area of focus for studying higher-order skills is decision-making. Effective decision-making requires people to consider alternative states of the world and the likely benefits and costs of different actions. Decision-making requires workers to synthesize information, apply knowledge to new situations, and test and evaluate evidence. These are clearly higher-order skills as in Bloom et al. (1956), so we should expect such skills to improve decision-making. For example, the counterfactual reasoning required to make decisions is cognitively taxing, which may explain the correlation between intelligence and patience (Dohmen et al., 2018).

Caplin et al. (2023) develop a measure of decision-making skill based on a model where workers make choices by strategically acquiring costly information under time and attention constraints. They find that economic decision-making skill predicts labor income in the U.S. and Denmark independent of education, IQ, numeracy and other factors, and that it is a better predictor of income in decision-intensive occupations like management. Fe et al. (2022) find that "theory of mind", or the ability to attribute mental states to others, predicts strategic sophistication in strategic decision-making games among young children in England.

A systematic approach to studying higher-order skills allows future studies to more easily build on past insights. For example, Weidmann et al. (2024) extend the method of Weidmann and Deming (2021) to identify the causal contribution of managers to team performance. They find that good managers have about twice the impact on team performance as good workers, and that the measure of economic decision-making skill developed and tested in Caplin et al. (2023) is a strong predictor of managerial performance. Interestingly, they also find that managers who nominate themselves for the role perform worse than those who are randomly assigned, in part because they are overconfident about their social skills as measured by the RMET test discussed above.

Can decision-making skill be improved with practice? Interventions like cognitive behavioral therapy (CBT) make people slow down, evaluate the consequences of their automatic behavior patterns, and reprogram new behaviors through deliberate practice. This improves decision-making by raising the cost of "bad" automatic behaviors and lowering the cost of "good" automatic behaviors. Heller et al. (2017) find large reductions in violent crime and increases in high school graduation from CBT interventions with high risk young men in Chicago. Blattman et al. (2023) find that CBT reduced violence among criminally engaged men in Liberia, with impacts that persisted for a decade and exceeded the impact of a cash grant. A few papers study the impact of decision-making skill in healthcare, where doctors have procedural skill but also diagnostic skill, and the latter is an important determinant of patient outcomes (Currie and MacLeod, 2017; Chan et al., 2022). Goldfarb and Xiao (2011) and Hortaçsu et al. (2019) find that education and other proxies for skill improve managerial decision-making.

Higher-order skills like teamwork and decision-making are clearly valuable in the labor market and are conceptually distinct in important ways from how cognitive skills are traditionally modeled by economists. How do higher-order skills fit into human capital theory?

The most flexible approach treats human capital as a mulitdimensional vector with weights that vary across occupations, industries, firms, or periods of time. We will call this the "skill weights" approach, following Lazear (2009). Heckman et al. (2006a) and Cunha and Heckman (2007) allow "cognitive' and "non-cognitive" skills to enter the production function for human capital and to matter more or less in different periods of childhood. Lise and Postel-Vinay (2020) develop a structural model of search and on-the-job learning where workers sort into occupations based on cognitive, manual, and interpersonal skills. They estimate the model using NLSY79 data and find distinct patterns of sorting and dynamic returns to each type of skill. Guvenen et al. (2020) estimate a dynamic model of occupational choice to identify the career consequences of multidimensional skill mismatch. More broadly, a large literature studies specific human capital and the extent to which it transfers across specific job tasks, occupations, and sectors of the economy (Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Pavan, 2011; Sanders and Taber, 2012; Taber and Vejlin, 2020). Other papers, too numerous to discuss here, focus on the linkage between field of study or college major and specific human capital (Kinsler and Pavan, 2015; Kirkeboen et al., 2016; Dahl et al., 2023; Deming and Noray, 2020; Silliman and Virtanen, 2022).

The advantage of a "skill weights" approach to modeling higher-order skills is flexibility. The disadvantage is that it is agnostic about how higher-order skills matter and in what contexts. In the next section we present a more specific, theory-driven approach to modeling how higher-order skills matter for human capital. We argue that skills like teamwork and decision-making are best understood in a context where workers are *agents* who make decisions about which job tasks to perform, and with whom. Standard human capital theory, including the "skill weights" approach described above, treats workers as factors of production, similar to physical capital. Higher human capital augments the marginal product of labor in job tasks, but the choice of tasks is implicit. This is a useful abstraction in many cases, but we argue that it is an increasingly inadequate description of what workers actually do and what makes them valuable.

5 Higher order skills and workers as agents

5.1 Team production and social skills

A growing body of evidence discussed in Section 4 suggests that measures of sociability and extraversion are positively related to labor market success. We could enter "social skills" into a multidimensional vector of human capital. This generates consistent empirical results across multiple countries and contexts, but it doesn't help us understand *why* social skills matter.

Deming (2017) develops a model where social skills reduce coordination costs in team production, which allow workers to better collaborate to exploit comparative advantage. The model generates specific predictions such as complementarity between social skills and task productivity, and relatively higher returns in non-routine occupations. The specific mechanism in the model involves team production with workers coordinating between themselves on a division of labor. In the model, social skills reduce coordination frictions and allow workers to better exploit comparative advantage in production.

We briefly develop the model below. See Deming (2017) for a full derivation of the main results and many additional details.[12] The worker's production function for any task i is:

$$y_j(i) = A_j \alpha_j(i) l_j(i) \tag{10}$$

Worker j's output for task i is equal to their overall ability (or cognitive skill) A_j times their productivity in the specific task $\alpha_j(i)$ times $l_j(i)$, the labor supplied to task i. Workers supply a single unit of labor inelastically to the production of a continuum of tasks indexed over the unit interval with a Cobb-Douglas technology.[13]

This setup allows scope for comparative advantage, because workers with the same average skill level A_j can vary in their productivity over individual tasks. Workers can increase their output Y_j by producing tasks in which they have a comparative advantage and "trading" them with other workers for mutual benefit, just as countries trade goods.

However, coordination is costly. Deming (2017) models social skills as inverse "iceberg" trade costs as in Dornbusch et al. (1977) and Eaton and Kortum (2002). Let $S_{j,k} \in (0, 1)$ be a depreciation factor applied to any task trade between workers, so that $S_{j,k} = S_j * S_k$ for $j \neq k$ and $S_{j,j} = 1$ so that self-trade is costless. Workers with higher social skills pay a lower coordination cost to trade tasks with others, allowing them to earn higher wages by specializing in their most productive tasks. This grounds the value of social skills in economic theory.

The key innovation of Deming (2017) relative to existing models is that workers produce output *together*. Although the model itself abstracts away from the details, we can imagine a process in which workers recognize that there are benefits to a division of labor between them and then decide whether to pay the coordination cost (e.g. meetings, calendar alignment, etc.). Discovering co-workers' comparative advantage and coordinating with them on team production can all be captured by the term $S_{j,k}$. If the coordination cost is too high, workers decide to produce alone instead, and do not gain the benefits of specialization.

To build intuition, consider the decision to produce alone or co-produce in the simple two-worker case. Identical firms hire pairs of workers and pay market wages equal to output Y_j times an exogenous output price P^*. Workers maximize output subject to their labor supply constraint, and

[12]The interested reader may also find a further formal depiction of the model in the Online Appendix of Deming (2017).

[13]The production function is $Y_j = exp[\int_0^1 \ln y_j(i) di]$, subject to the constraint that labor supply adds up to 1 across all tasks, e.g. $L_j = \int_0^1 l_j(i) di = 1$.

firms maximize total revenue minus wages, e.g. $P^*[(Y_1 + Y_2)] - (w_1 + w_2)$.

Define the comparative advantage schedule for worker 1 relative to worker 2 as:

$$\gamma_i = \frac{A_1 \alpha_1(i)}{A_2 \alpha_2(i)} \tag{11}$$

and arrange the continuum of tasks in order of decreasing comparative advantage for worker 1, so that $\gamma^{'}(i) < 0$ by construction. Deming (2017) assumes $\gamma(i) = \frac{A_1}{A_2} \exp \theta(1 - 2i)$ for concreteness, although that specific functional form is not necessary for the main predictions of the model to hold. The parameter θ indexes the variance of task productivity and thus the steepness of the comparative advantage schedule $\gamma(i)$. As $\theta \to 0$, workers with higher cognitive skill A_i are more productive in all tasks, and there is no scope for gains from task trade.

Each worker maximizes their wages by obtaining tasks from the lowest cost producer, including themselves. If task trade is costless (e.g. $S_{j,k} = 1$), each worker's "price" of supplying a task is:

$$p_j(i) = \frac{w_j}{A_j \alpha_j(i)} \tag{12}$$

where w_j is the endogenously determined wage for worker j. Since the equilibrium task price is always the lowest between the two workers, and since $\gamma^{'}(i) < 0$ and there is a smooth continuum of tasks, there will always be a marginal task i^* that determines the division of labor. Worker 1 performs all tasks in the interval $[0, i^*]$ and worker 2 performs all tasks in the interval $[i^*, 1]$.

In equilibrium, relative wages $\omega = \frac{w_1}{w_2}$ depend on the share of the task continuum performed by each worker:[14]

$$\omega = \frac{i^*}{1 - i^*} \tag{13}$$

The equilibrium with social skills involves two task thresholds i^L and i^H and an untraded zone of tasks where the cost of coordinating outweights the benefits of comparative advantage. Define $S^* = S_1 + S_2$ as the symmetric cost of trading tasks between workers 1 and 2, with self-trade normalized to 1 as above. Worker 1 will produce their own tasks rather than trading if the "price" of doing so is lower, e.g. if:

$$\frac{w_1}{A_1 \alpha_1(i)} < \frac{w_2}{S^* A_2 \alpha_2(i)} \tag{14}$$

If we rearranging terms to solve for the relative wage, we find that worker 1 produces their own tasks rather than trading when $\omega < \frac{\gamma_i}{S^*}$. Worker 2 will self-produce when $\omega > S^* \gamma_i$. Solving for γ_i in both inequalities yields the two task thresholds $\frac{\omega}{S^*}$ and $S^* \omega$ for i^L and i^H respectively. Tasks in

[14] In equilibrium, the price-adjusted quantity of output for the marginal task i^* must be the same for both workers, and the Cobb-Douglas production function implies that the same share of output is paid to each task. Equilibrium is found by setting the expression for comparative advantage above equal to the expression for the marginal task i^*. See Deming (2017) for details.

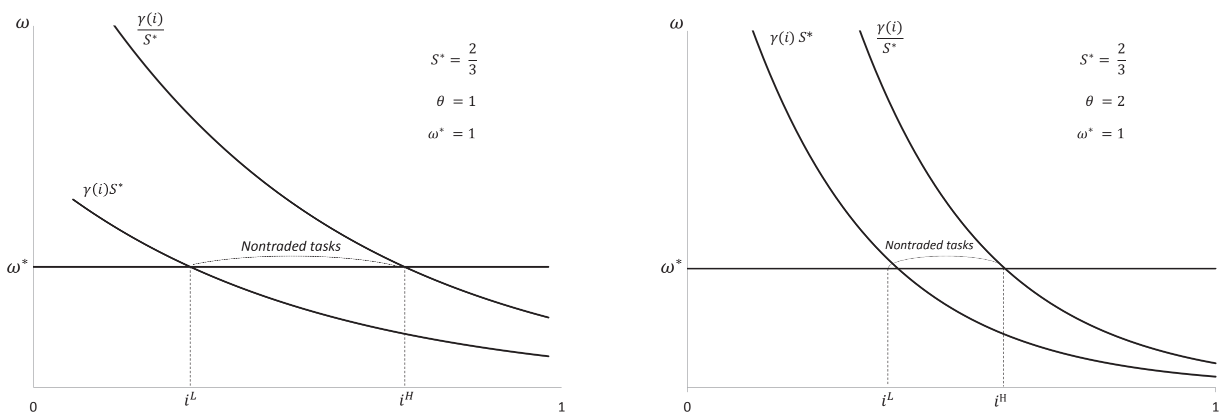
the interval $(0, i^L)$ will be produced by worker 1, tasks in the interval $(i^H, 1)$ will be produced by worker 2, and tasks in the interval (i^L, i^H) will be nontraded (e.g. self-produced). As $S^* \to 1$, the two task thresholds converge to a single point i^* as when task trade is costless. Solving the two task thresholds for ω yields an expression for the share of tasks that are nontraded:

$$i^H - i^L = -\frac{\ln S^*}{\theta} \tag{15}$$

The above equation shows that the size of the nontraded zone $i^H - i^L$ is decreasing in θ and inversely scales the gains from trade. This point is depicted visually in Figure 1, which shows the size of the nontraded zone with different values of θ.

Figure 1: Equilibrium Task Thresholds with Different Values of Theta

(a) (b)



Notes: Panel A illustrates the equilibrium task thresholds i^L and i^H from the model above when $S^* = \frac{2}{3}, \theta = 1, and \omega^* = 1$. Panel B illustrates the equilibrium task thresholds i^L and i^H from the model above when $S^* = \frac{2}{3}, \theta = 1, and \omega^* = 1.$. See the original paper for more details (Deming, 2017).

There are many values of S^* and θ for which the size of the nontraded zone exceeds 1, which corresponds to the absence of trade (e.g. autarky) and all workers producing their own tasks. In general, the economic return to social skills in increasing in θ, the variance of productivity draws. Deming (2017) shows that social skills are more valuable in non-routine occupations and argues that this is consistent with the interpretation of θ in the model.

Also, the model predicts that cognitive skill A_j and social skill S_j will be complements in a wage equation, because reducing coordination costs is more beneficial when workers have higher value tasks to "trade". This prediction contrasts with multidimensional assignment models of human capital, which typically assume separability of skills in the wage equation for tractability (Lindenlaub, 2017; Lise and Postel-Vinay, 2020). Deming (2017) finds a positive and statistically significant interaction between cognitive skills and social skills using NLSY data, but does not find the same complementarity between cognitive skills and the measures of non-cognitive skills used by Heckman et al. (2006a).

Several recent papers consider worker complementarities in team production. In Herkenhoff et al. (2024) and Jarosch et al. (2021), workers learn from each other and having highly productive coworkers increases future wage growth because of human capital spillovers. Jäger and Heining (2022) show that the unexpected death of workers in high- skilled occupations has a negative impact on other workers in the same firm, suggesting that workers are complements in production. Freund (2022) develops a model of team production with task specialization and comparative advantage and finds that growing sorting and worker skill complementarity generates a substantial share of the increase in wage inequality and firm productivity dispersion in Germany since the mid 1980s. Lyons (2017) finds that teamwork is more productive when co-workers share the same nationality because diverse teams have more difficulty communicating.

Overall, the model in Deming (2017) generates significantly richer predictions than simply including social skills as one element among many in the human capital vector. The key insight is that workers are choosing a division of labor between them, and whether it is worth it to work together or go it alone. While the model above is deliberately simple, it can be generalized to consider many other skills and to include multiple workers, among other extensions.

5.2 Decision-making skills

As we discussed in Section 4.3, firms value workers who are good decision-makers and problem solvers, and there is a high and growing economic return to being able to make good decisions on the job. An older literature in economics studies "allocative ability", particularly related to technology adoption in agriculture (Nelson and Phelps, 1966; Welch, 1970). Yet most models of human capital focus on productive rather than allocative ability.

A standard approach measures the worker's human capital – call it α_j – using years of education, cognitive test scores, or some other metric. Implicitly, human capital captures *productive* efficiency, or the marginal product of labor. Caplin et al. (2023) consider a decision-maker assigning workers to different tasks to maximize output. Workers have heterogeneous productivity schedules over tasks, which are costly to observe. The decision-maker must allocate their scarce attention to the most important features of the decision-problem. They argue that people have different attention costs, and they call the ability to deploy attention well (e.g. the marginal product of attention) *economic decision-making skill*.

We illustrate the value of modeling workers as decision-makers with a simple conceptual model that is derived from Caplin et al. (2023). We keep the exposition deliberately simple to illustrate our main point and leave extensions of the basic model to future work.

Again consider the benchmark model where α_j measures worker j's productivity, either overall or in a particular task. Suppose that workers can choose between two ways of performing any task – a safe technology with known output $\alpha_j = \alpha$, or an uncertain or novel technology that yields $\alpha_j = \alpha_j * x$, where x is an unknown random state. We assume that the expected value of x is one, so that workers are *ex ante* indifferent between technologies.

We can think of this as modeling "problem solving" on the job, in the sense that workers are confronted with novel problems that require adaptation to some local context that only they can observe. Dessein and Santos (2006) consider the optimal amount of discretion granted to workers from the firm's perspective. Adaptive organizations allow workers the flexibility to choose actions in response to local context, while centralized organizations adopt strict rules that coordinate on a minimum standard of performance that does not allow for responsiveness. They show that the optimal level of adaptation is increasing in workers' ability to succeed in highly bundled jobs, meaning jobs where a broad range of actions may be required in response to local information shocks. In other words, workers who are good problem-solvers and decision-makers (Deming, 2021).

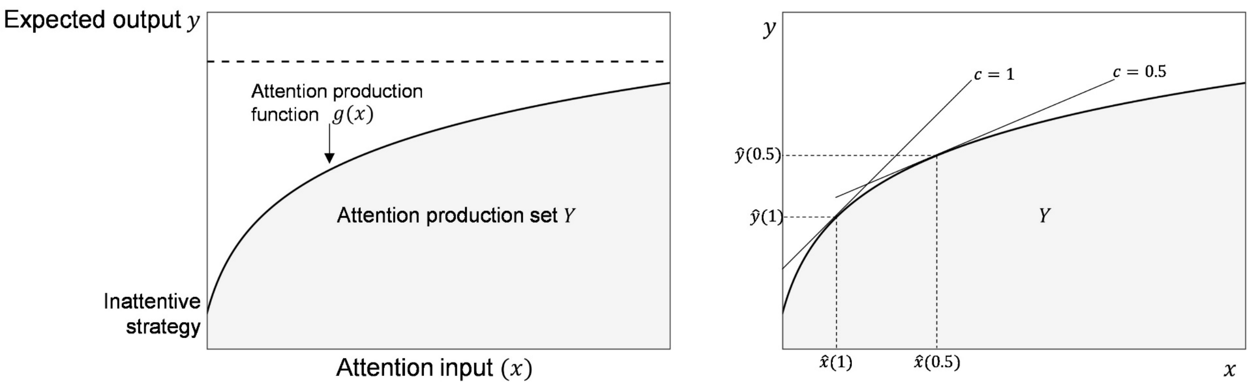
Workers begin with some prior belief and *ex ante* uncertainty about the local context, represented by the distribution $g(x)$, and then optimally invest in acquiring costly information to refine their beliefs about x. We can represent the worker's production function as:

$$y_j = f(\alpha_j | x) \tag{16}$$

$f(\alpha_j|x)$ describes how the worker's choice of technology depends on the information they receive about the local context. Intuitively, if information acquisition is extremely costly, the worker will default to the same approach every time, meaning they will choose a response function f that does not depend on x (e.g. $f(\alpha_j|x)$ will be degenerate). The better they are at acquiring information, the more sensitive their responses will be to it. If the worker observes x perfectly, they will always pick the uncertain technology when the context is favorable (e.g. $x \geq 1$) and the safe technology otherwise.

This point is shown visually in Figure 2, which relates attentional inputs to productivity. With random guessing, the expected output is very low – i.e. the intercept to the vertical axis. As a person is better capable of acquiring the information relevant for making decisions, their productivity will increase. The righthand panel shows that lower attention costs will shift people to make better choices, and thereby become more productive.

Figure 2: Attention Inputs and Productivity with Varying Attention Costs



Notes: Figure 2 (originally in Caplin et al. (2023) presents a graphical illustration of the attention production set Y, which maps the space of possible outputs the decision-maker can achieve for any fixed amount of x. The vertical axis intercept corresponds to output under a fully inattentive strategy (e.g. random guessing.) The production function $g(x)$ maps the frontier of expected output for any given input. The righthand panel depicts the impact of a decrease in the marginal cost of attention from $c = 1$ to $c = 0.5$, which flattens the slope of the tangency line and causes the agent to optimally pay more attention and produce higher expected output. See Sections 2.1-2.3 of Caplin et al. (2023) for further details.

We can model the worker's choice of technology as a two-step process. First they acquire a set of costly signals that help them refine their prior beliefs about x. Second, they choose the optimal α_j given their posterior beliefs.[15]

The worker chooses $f(\alpha_j|x)$ to maximize expected output subject to the cost of acquiring information $K(f)$:[16]

$$K(f) = c_j I(y_j; x) \tag{17}$$

with $I(y_j; x)$ as the Shannon mutual information between y_j and x.[17] Intuitively, $I(y_j; x)$ measures the extent to which the worker's response function $f(\alpha_j|x)$ reduces their uncertainty about the state

[15]Since an optimal response function requires that no two sets of signals lead to the same action, we do not need to model their signal choice explicitly and can work directly with $f(\alpha_j|x)$ (Sims, 2003; Kamenica and Gentzkow, 2011; Maćkowiak et al., 2023).

[16]Another constraint in the maximization problem is Bayesian rationality, meaning posterior beliefs must be consistent with prior beliefs, e.g. $g(x) = \int f(y|x)g(x|y)dy$.

[17]Mutual information is defined as $I(y_j; x) = H(x) - E[H(x|y)]$ where $H(x)$ is the entropy of the random state x.

x.

$c_j > 0$ measures the cost of acquiring information. For ease of interpretation we define its inverse $\phi_j = \frac{1}{c_j}$ as the worker's information processing efficiency, or decision-making skill. Workers with higher ϕ_j are better decision-makers because they are more likely to figure out the correct action for any given context x.

We assume that every worker has prior beliefs that are unbiased and normally distributed with a common variance, e.g. $g(x) \sim N(0, \sigma_x^2)$.[18] We further assume that the worker receives a normally distributed signal $s = x + \epsilon$, where ϵ is independent of x and $\epsilon \sim N(0, \sigma_\epsilon^2)$.[19] These assumptions simplify the exposition considerably. For a more general model with many possible actions and a more flexible formulation of beliefs, see Caplin et al. (2023).

Higher values of the signal variance σ_ϵ^2 mean that information gathering is more difficult. We can think of σ_ϵ^2 as representing the complexity or difficulty of the decision problem. The expected output from choosing the safe action is just α_i, as in the standard human capital model. We can write the expected output from choosing the risky action as:

$$E[f\alpha_j|x)] - K(f) = (\frac{\sigma_x^2}{\sigma_x^2 + \sigma_\epsilon^2})\alpha_i s - \log(\frac{\sigma_x^2 + \sigma_\epsilon^2}{\sigma_\epsilon^2})\frac{1}{2\phi_j} \tag{18}$$

The worker prefers the risky action if its expected value exceeds α_j, which in turn depends on the balance between the first and second terms in equation above. The first term captures the benefits of the risky action. which is just the worker's baseline productivity α_j times the signal s that they receive about the state x, weighted by the ratio $(\frac{\sigma_x^2}{\sigma_x^2+\sigma_\epsilon^2})$, which measures their confidence in the quality of the information they've gathered about x. As σ_ϵ^2 increases the worker becomes less confident about x, which decreases the expected benefit of choosing the risky action for any estimate of s.

The second term in equation (18) measures the cost of information gathering. Workers with higher ϕ_j pay a lower cost to acquire information and thus have higher expected benefits from choosing the risky action.[20]

Moreover, σ_ϵ^2 and ϕ_j are complements, which implies that decision-making skills matter more for complex decision problems when signals are noisier and information is harder to acquire.

Workers choose the risky action only when the expected output in equation (18) is greater than

[18] The model can be enriched by adding differences between workers in the bias and variance of prior beliefs, perhaps through accumulated experience. We leave this as an exercise for the reader.

[19] This means that s is also normally distributed, with $s \sim N(0, \sigma_x^2 + \sigma_\epsilon^2)$. Using the mutual information formula for the normal distribution, we have $I(y_j; x) = \frac{1}{2}\log(\frac{\sigma_x^2+\sigma_\epsilon^2}{\sigma_\epsilon^2})$.

[20] The derivative of equation (18) with respect to ϕ_j is equal to $\log(\frac{\sigma_x^2+\sigma_\epsilon^2}{\sigma_\epsilon^2})\frac{1}{2\phi_j^2}$, which is always positive since $\phi_j > 0$ and the term in parentheses is always greater than or equal to one.

α_j. Thus, the model collapses to the standard human capital model with productivity equal to α_j as decision problems become extremely difficult and for workers with very weak decision-making skills (e.g. as $\sigma_\epsilon^2 \to \infty$ and as $\phi_j \to 0$).

More generally, the minimum value of the signal s required to make the worker choose the risky action is decreasing in α_j and ϕ_j.[21] In other words, all else equal, workers with greater decision-making skill and productive skill are more likely to choose the risky action overall and have higher expected output.

Caplin et al. (2023) estimate ϕ_j using a novel decision-making assessment administered to full-time workers in the U.S. and Denmark. They show that ϕ_j, which they call *economic decision-making skill*, predicts full-time labor earnings for workers in both countries, and that is a better predictor of earnings in decision-intensive occupations. The model in Caplin et al. (2023) generalizes to many actions rather than just two. They also show that performance suffers when the complexity of the decision problem increases, and that decision-makers respond to complexity with inattention and simple heuristics.[22]

Overall, this simple model shows how the higher-order skill of decision-making under uncertainty can be incorporated into an otherwise standard human capital model. Future work could extend the approach to multiple actions or consider the importance of prior beliefs and biases. An interesting implication of the theory is that biased priors will be stickier for workers with poor decision-making skills, because they are less responsive to new information. We leave this and other extensions for future work.

In this section we have presented two examples of how modeling workers as decision-making agents admits a broader definition of human capital and allows for rich explorations of how higher-order skills matter. We considered models of teamwork and decision-making skills. Future work could explore other skills like grit (e.g. how much effort a worker decides to exert on a particular task versus switching to some alternative approach) or self-awareness (how does a worker update their beliefs about their own ability in response to new information). Importantly. the models in Section 5 say nothing about where higher-order skills come from or how they can be developed. This is also an important area for future work.

[21] The exact condition is $s > (\frac{\sigma_x^2+\sigma_\epsilon^2}{\sigma_x^2})(1 + \frac{1}{2\alpha_i\phi_j} \log(\frac{\sigma_x^2+\sigma_\epsilon^2}{\sigma_\epsilon^2})$, which is bounded below at 1 when information is costless to acquire and the ratio $(\frac{\sigma_x^2}{\sigma_x^2+\sigma_\epsilon^2})$ approaches unity, and is decreasing in α_j and ϕ_j.

[22] Oprea (2020) formally studies the complexity of a decision problem and shows that the number of potential states in a decision problem is an important indicator of complexity. Consistent with Oprea (2020), Caplin et al. (2023) find that participants perform much worse when assignment problems are 4x4, with 24 possible states, rather than 3x3 with only 6 possible states.

6 Conclusion

Human capital, skills, and education have been a central area of study for labor economists trying to understand the sources of earnings differences between people and the wage structure of an economy. This chapter provides an overview of what economists know about skills and human capital in the labor market.

Section 2 briefly summarizes the vast number of studies that produce microeconomic estimates of the return to education and connects them to the "macro" literature on how the supply and demand for skills affects the wage structure of an economy. Averaging over thousands of descriptive and quasi-experimental studies, the economic return to an additional year of education turns out to be around ten percent. Education alone explains about one-third of earnings variation between workers. Total human capital - including years of education but also other unobserved human capital - explains at least half of the variation in labor earnings.

The average return to schooling of ten percent per year is not an iron law of economics. Rather it reflects the average equilibrium price of skill in economies that balance supply against demand. The "canonical model" explains the evolution of the college wage premium in the U.S. and other countries as the outcome of a race between rising skill supply (e.g. more of the workforce obtaining a college degree) and growing skill demand (e.g. new technologies making educated workers relatively more productive). We develop a basic version of the canonical model as in Katz and Murphy (1992) and Goldin and Katz (2007) and discuss how well it fits the data in the U.S. and around the world over the last century. Finally, Section 2 also provides a brief overview of the literature on human capital and cross-countries differences in earnings and productivity.

Section 3 explores what is known about human capital development. We provide a brief treatment of the classic model of Ben-Porath (1967), which explores the optimal timing of human capital investment over the life cycle. The Ben-Porath model provides an economic rationale for early life human capital investment. The life-cycle skill formation model of Cunha and Heckman (2007) provides a *technological* rationale for early investment by arguing that skill investment is self-productive (e.g. skills beget skills) and that early life deficits are very costly or impossible to remediate later (e.g. dynamic complementarity). We develop the Cunha and Heckman (2007) model briefly and then present empirical evidence suggesting that skill investments appear to be equally productive throughout childhood and early adulthood. This does not invalidate the model altogether, but it does suggest that more work is needed to identify and estimate the technology of skill formation.

Section 4 presents evidence for the growing importance and economic value of "non-cognitive" skills. Many studies have found a strong association between labor market earnings and various measures of personality traits and preferences. Over the last two decades, the economic returns to cognitive skills have been flat or declined in the U.S., Sweden, and Finland, while the returns to "non-cognitive" or "soft" skills like conscientiousness, extraversion, emotional stability, and social skills have grown rapidly (Deming, 2017; Edin et al., 2022; Izadi and Tuhkuri, 2024). We argue that the right term for these capacities is "higher order" skills, in part because they are farther up the hierarchy of cognitive processes than the skills measured by traditional tests of academic achievement. Teamwork and decision-making require workers to apply knowledge to solving new problems and to connect one's own skills and ideas to others. This requires a deeper understanding of how skills relate to worker productivity. In particular, we argue that modeling higher order skills requires us to consider workers as agents who make choices about which jobs or tasks to do, and whether to do them alone or in a team. Section 5 illustrates the value of this approach by developing two simple models of teamwork and decision-making respectively, where higher-order skills govern the choice of tasks and productive skills augment the marginal product of labor as usual.

Our review suggests promising directions for future research. While there are many studies that demonstrate the correlation between earnings and off-the-shelf survey measures of personality traits or preferences like extraversion, conscientiousness, and patience, relatively few studies combine such evidence with rigorous, testable theories of *how* higher order skills matter, for whom, and in which contexts. Understanding how higher order skills fit into the human capital production function will improve scientific understanding, but it also has obvious policy relevance. For example, are there tradeoffs between teaching basic and higher-order skills to children, or to adults? Is it necessary to master basic skills before learning higher-order skills? Can teamwork and decision-making skills be improved with practice, and if so, what is the optimal timing of investment over the life-cycle? Which occupations, industries, and firms require such skills more intensively, and can they be learned on-the-job? These and many other questions are promising avenues for further study.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in us wage inequality. *Econometrica*, 90(5):1973–2016.

Acevedo, P., Cruces, G., Gertler, P., and Martinez, S. (2020). How vocational education made women better off but left men behind. *Labour Economics*, 65:101824.

Adda, J. and Dustmann, C. (2023). Sources of wage growth. *Journal of Political Economy*, 131(2):456–503.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2023). Returns to on-the-job soft skills training. *Journal of Political Economy*, 131(8):2165–2208.

Aghion, P., Bergeaud, A., Blundell, R. W., and Griffith, R. (2024). Social skills and the individual wage growth of less educated workers. *INSEAD Working Paper*.

Agostinelli, F. and Wiswall, M. (2016). Estimating the technology of children's skill formation. Technical report, National Bureau of Economic Research.

Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, 130(4):1781–1824.

Alan, S., Boneva, T., and Ertac, S. (2019). Ever failed, try again, succeed better: Results from a randomized educational intervention on grit. *The Quarterly Journal of Economics*, 134(3):1121–1162.

Alan, S. and Ertac, S. (2018). Fostering patience in the classroom: Results from randomized educational intervention. *Journal of Political Economy*, 126(5):1865–1911.

Algan, Y., Beasley, E., Côté, S., Vitaro, F., Tremblay, R. E., and Park, J. (2022). The impact of childhood social skills and self-control training on economic and non-economic outcomes: Evidence from a randomized experiment using administrative data. *American Economic Review*.

Allemand, M., Kirchberger, M., Milusheva, S., Newman, C., Roberts, B., and Thorne, V. (2023). Conscientiousness and labor market returns.

Almås, I., Attanasio, O., and Jervis, P. (2023). Economics and measurement: New measures to model decision making. Technical report, National Bureau of Economic Research.

Almond, D. and Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of Economic Perspectives*, 25(3):153–172.

Almond, D., Currie, J., and Duque, V. (2018). Childhood circumstances and adult outcomes: Act ii. *Journal of Economic Literature*, 56(4):1360–1446.

Angrist, J. D. and Krueger, A. B. (1991). Does compulsory school attendance affect schooling and earnings? *The Quarterly Journal of Economics*, 106(4):979–1014.

Arcidiacono, P., Kinsler, J., and Price, J. (2017). Productivity spillovers in team production: Evidence from professional basketball. *Journal of Labor Economics*, 35(1):191–225.

Arellano-Bover, J. and Saltiel, F. (2024). Differences in on-the-job learning across firms.

Arteaga, C. (2018). The effect of human capital on earnings: Evidence from a reform at colombia's top university. *Journal of Public Economics*, 157:212–225.

Aryal, G., Bhuller, M., and Lange, F. (2022). Signaling and employer learning with instruments. *American Economic Review*, 112(5):1669–1702.

Ashraf, N., Bau, N., Low, C., and McGinn, K. (2020). Negotiating a better future: How interpersonal skills facilitate intergenerational investment. *The Quarterly Journal of Economics*, 135(2):1095–1151.

Attanasio, O., Cattan, S., Fitzsimons, E., Meghir, C., and Rubio-Codina, M. (2020). Estimating the production function for human capital: results from a randomized controlled trial in colombia. *American Economic Review*, 110(1):48–85.

Attanasio, O., Cattan, S., and Meghir, C. (2021). Early childhood development, human capital and poverty. Technical report, National Bureau of Economic Research.

Autor, D. (2017). How long has this been going on? a discussion of 'recent flattening in the higher/education wage premium: Polarization, skill downgrading, or both?'by robert g. valletta. In *NBER Conference on Research and Income in Wealth "Measuring and Accounting for Innovation in the 21st Century," Washington, DC (March 10–11, 2017)*, volume 2.

Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. (2022). New frontiers: The origins and content of new work, 1940–2018. Technical report, National Bureau of Economic Research.

Autor, D., Goldin, C., and Katz, L. F. (2020). Extending the race between education and technology. In *AEA Papers and Proceedings*, volume 110, pages 347–351. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in us wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2):300–323.

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

Bailey, D. H., Duncan, G. J., Cunha, F., Foorman, B. R., and Yeager, D. S. (2020). Persistence and fade-out of educational-intervention effects: Mechanisms and potential solutions. *Psychological Science in the Public Interest*, 21(2):55–97.

Barbosa, R. (2023). Effect of school management improvements on the student's social and emotional skills: Experimental evidence from brazil. *Available at SSRN 4845841*.

Baron-Cohen, S., Wheelwright, S., Hill, J., Raste, Y., and Plumb, I. (2001). The "reading the mind in the eyes" test revised version: a study with normal adults, and adults with asperger syndrome or high-functioning autism. *The Journal of Child Psychology and Psychiatry and Allied Disciplines*, 42(2):241–251.

Barrera-Osorio, F., Kugler, A., and Silliman, M. (2023). Hard and soft skills in vocational training: Experimental evidence from colombia. *The World Bank Economic Review*, 37(3):409–436.

Bastian, J. and Michelmore, K. (2018). The long-term impact of the earned income tax credit on children's education and employment outcomes. *Journal of Labor Economics*, 36(4):1127–1163.

Beaudry, P., Green, D. A., and Sand, B. M. (2016). The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics*, 34(S1):S199–S247.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(5, Part 2):9–49.

Becker, G. S. (2007). Health as human capital: synthesis and extensions. *Oxford Economic Papers*, 59(3):379–410.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 75(4, Part 1):352–365.

Berman, E., Bound, J., and Machin, S. (1998). Implications of skill-biased technological change: international evidence. *The Quarterly Journal of Economics*, 113(4):1245–1279.

Betts, J. R. (1997). The skill bias of technological change in canadian manufacturing industries. *Review of Economics and Statistics*, 79(1):146–150.

Bhuller, M., Mogstad, M., and Salvanes, K. G. (2017). Life-cycle earnings, education premiums, and internal rates of return. *Journal of Labor Economics*, 35(4):993–1030.

Bils, M., Kaymak, B., and Wu, K.-J. (2022). Labor substitutability among schooling groups. Technical report, National Bureau of Economic Research.

Bils, M. and Klenow, P. J. (2000). Does schooling cause growth? *American Economic Review*, 90(5):1160–1183.

Blandin, A. (2018). Learning by doing and ben-porath: Life-cycle predictions and policy implications. *Journal of Economic Dynamics and Control*, 90:220–235.

Blattman, C., Chaskel, S., Jamison, J. C., and Sheridan, M. (2023). Cognitive behavioral therapy reduces crime and violence over ten years: Experimental evidence. *American Economic Review: Insights*, 5(4):527–545.

Bloom, B. S., Engelhart, M. D., Furst, E., Hill, W. H., and Krathwohl, D. R. (1956). Handbook i: cognitive domain. *New York: David McKay*, pages 483–498.

Bonhomme, S. (2021). Teams: Heterogeneity, sorting, and complementarity. *arXiv preprint arXiv:2102.01802*.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, 43(4):972–1059.

Brown, C. L., Kaur, S., Kingdon, G., and Schofield, H. (2022). Cognitive endurance as human capital. Technical report, National Bureau of Economic Research.

Brudevold-Newman, A. and Ubfal, D. J. (2023). *Returns to Soft Skills Training in Rwanda*. World Bank.

Campbell, F., Conti, G., Heckman, J. J., Moon, S. H., Pinto, R., Pungello, E., and Pan, Y. (2014). Early childhood investments substantially boost adult health. *Science*, 343(6178):1478–1485.

Caplan, B. (2019). The case against education: Why the education system is a waste of time and money.

Caplin, A., Deming, D. J., Leth-Petersen, S., and Weidmann, B. (2023). Economic decision-making skill predicts income in two countries. Technical report, National Bureau of Economic Research.

Card, D. (1993). Using geographic variation in college proximity to estimate the return to schooling.

Card, D. (1999). The causal effect of education on earnings. *Handbook of Labor Economics*, 3:1801–1863.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Carlana, M. and La Ferrara, E. (2024). Apart but connected: Online tutoring, cognitive outcomes, and soft skills. Technical report, National Bureau of Economic Research.

Carlsson, M., Dahl, G. B., Öckert, B., and Rooth, D.-O. (2015). The effect of schooling on cognitive skills. *Review of Economics and statistics*, 97(3):533–547.

Carneiro, P., Cruz-Aguayo, Y., Pachon, R. H., and Schady, N. (2022a). Dynamic complementarity in elementary schools: Experimental estimates from ecuador. Technical report, Working Paper.

Carneiro, P., Heckman, J. J., and Vytlacil, E. J. (2011). Estimating marginal returns to education. *American Economic Review*, 101(6):2754–2781.

Carneiro, P. M. and Heckman, J. J. (2003). Human capital policy.

Carneiro, P. M., Salvanes, K. G., Willage, B., and Willén, A. (2022b). The timing of parental job displacement, child development and family adjustment. *NHH Dept. of Economics Discussion Paper*, (12).

Cascio, E. U. and Lewis, E. G. (2006). Schooling and the armed forces qualifying test: Evidence from school-entry laws. *Journal of Human resources*, 41(2):294–318.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth*, 1:679–741.

Caselli, F. and Ciccone, A. (2019). The human capital stock: A generalized approach: Comment. *American Economic Review*, 109(3):1155–1174.

Castex, G. and Kogan Dechter, E. (2014). The changing roles of education and ability in wage determination. *Journal of Labor Economics*, 32(4):685–710.

Caucutt, E. M. and Lochner, L. (2020). Early and late human capital investments, borrowing constraints, and the family. *Journal of Political Economy*, 128(3):1065–1147.

Chan, D. C., Gentzkow, M., and Yu, C. (2022). Selection with variation in diagnostic skill: Evidence from radiologists. *The Quarterly Journal of Economics*, 137(2):729–783.

Chari, V. V. and Hopenhayn, H. (1991). Vintage human capital, growth, and the diffusion of new technology. *Journal of Political Economy*, 99(6):1142–1165.

Chetty, R., Friedman, J. N., Hendren, N., Jones, M. R., and Porter, S. R. (2018). The opportunity atlas: Mapping the childhood roots of social mobility. Technical report, National Bureau of Economic Research.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., and Yagan, D. (2011). How does your kindergarten classroom affect your earnings? evidence from project star. *The Quarterly Journal of Economics*, 126(4):1593–1660.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014). Measuring the impacts of teachers ii: Teacher value-added and student outcomes in adulthood. *American economic review*, 104(9):2633–2679.

Chioda, L., Contreras-Loya, D., Gertler, P., and Carney, D. (2021). Making entrepreneurs: Returns to training youth in hard versus soft business skills. Technical report, National Bureau of Economic Research.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2):31–47.

Cunha, F. and Heckman, J. J. (2010). Investing in our young people. Technical report, National Bureau of Economic Research.

Currie, J. and MacLeod, W. B. (2017). Diagnosing expertise: Human capital, decision making, and performance among physicians. *Journal of labor economics*, 35(1):1–43.

Dahl, G. B., Rooth, D.-O., and Stenberg, A. (2023). High school majors and future earnings. *American Economic Journal: Applied Economics*, 15(1):351–82.

Deming, D. (2009). Early childhood intervention and life-cycle skill development: Evidence from head start. *American Economic Journal: Applied Economics*, 1(3):111–34.

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

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

Deming, D. J. (2021). The growing importance of decision-making on the job. Technical report, National Bureau of Economic Research.

Deming, D. J. (2022). Four facts about human capital. *Journal of Economic Perspectives*, 36(3):75–102.

Deming, D. J. (2023a). Multidimensional human capital and the wage structure.

Deming, D. J. (2023b). Why do wages grow faster for educated workers? Technical report, National Bureau of Economic Research.

Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and stem careers. *The Quarterly Journal of Economics*, 135(4):1965–2005.

Dessein, W. and Santos, T. (2006). Adaptive organizations. *Journal of Political Economy*, 114(5):956–995.

Deutscher, N. (2020). Place, peers, and the teenage years: long-run neighborhood effects in australia. *American Economic Journal: Applied Economics*, 12(2):220–249.

Dimitriadis, S. and Koning, R. (2020). Relational skills, endogenous matching, and business performance: A field experiment with entrepreneurs in togo. Technical report, Working Paper.

Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2018). On the relationship between cognitive ability and risk preference. *Journal of Economic Perspectives*, 32(2):115–134.

Dornbusch, R., Fischer, S., and Samuelson, P. A. (1977). Comparative advantage, trade, and payments in a ricardian model with a continuum of goods. *The American Economic Review*, 67(5):823–839.

Dube, O., MacArthur, S. J., and Shah, A. K. (2023). A cognitive view of policing. Technical report, National Bureau of Economic Research.

Duckworth, A. (2016). *Grit: The power of passion and perseverance*, volume 234. Scribner New York, NY.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American Economic Review*, 91(4):795–813.

Duncan, G. J. and Magnuson, K. (2013). Investing in preschool programs. *Journal of economic perspectives*, 27(2):109–132.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the german wage structure. *The Quarterly Journal of Economics*, 124(2):843–881.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Edin, P.-A., Fredriksson, P., Nybom, M., and Öckert, B. (2022). The rising return to noncognitive skill. *American Economic Journal: Applied Economics*, 14(2):78–100.

Fan, E., Meng, X., Wei, Z., and Zhao, G. (2018). Rates of return to four-year university education: An application of regression discontinuity design. *The Scandinavian Journal of Economics*, 120(4):1011–1042.

Fe, E., Gill, D., and Prowse, V. (2022). Cognitive skills, strategic sophistication, and life outcomes. *Journal of Political Economy*, 130(10):2643–2704.

Freund, L. (2022). Superstar teams: The micro origins and macro implications of coworker complementarities. *Available at SSRN 4312245*.

Garces, E., Thomas, D., and Currie, J. (2002). Longer-term effects of head start. *American Economic Review*, 92(4):999–1012.

García, J. L., Heckman, J. J., Leaf, D. E., and Prados, M. J. (2020). Quantifying the life-cycle benefits of an influential early-childhood program. *Journal of Political Economy*, 128(7):2502–2541.

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

Goldfarb, A. and Xiao, M. (2011). Who thinks about the competition? managerial ability and strategic entry in us local telephone markets. *American Economic Review*, 101(7):3130–3161.

Goldin, C. and Katz, L. F. (2007). The race between education and technology: the evolution of us educational wage differentials, 1890 to 2005.

Goldin, C. and Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

Goodman, J. (2019). The labor of division: Returns to compulsory high school math coursework. *Journal of Labor Economics*, 37(4):1141–1182.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–2526.

Gosling, A., Machin, S., and Meghir, C. (2000). The changing distribution of male wages in the uk. *The Review of Economic Studies*, 67(4):635–666.

Gray-Lobe, G., Pathak, P. A., and Walters, C. R. (2023). The long-term effects of universal preschool in boston. *The Quarterly Journal of Economics*, 138(1):363–411.

Gregory, V. (2020). Firms as learning environments: Implications for earnings dynamics and job search. *FRB St. Louis Working Paper*, (2020-036).

Griliches, Z. (1979). Sibling models and data in economics: Beginnings of a survey. *Journal of Political Economy*, 87(5, Part 2):S37–S64.

Groh, M., Krishnan, N., McKenzie, D., and Vishwanath, T. (2016). The impact of soft skills training on female youth employment: evidence from a randomized experiment in jordan. *IZA Journal of Labor & Development*, 5:1–23.

Gunderson, M. and Oreopolous, P. (2020). Returns to education in developed countries. In *The economics of education*, pages 39–51. Elsevier.

Guvenen, F., Kuruscu, B., Tanaka, S., and Wiczer, D. (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, 12(1):210–244.

Hall, R. E. and Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, 114(1):83–116.

Hanushek, E. A., Kinne, L., Lergetporer, P., and Woessmann, L. (2022). Patience, risk-taking, and human capital investment across countries. *The Economic Journal*, 132(646):2290–2307.

Hanushek, E. A. and Woessmann, L. (2012). Do better schools lead to more growth? cognitive skills, economic outcomes, and causation. *Journal of economic growth*, 17:267–321.

Heckman, J., Moon, S. H., Pinto, R., Savelyev, P., and Yavitz, A. (2010a). Analyzing social experiments as implemented: A reexamination of the evidence from the highscope perry preschool program. *Quantitative economics*, 1(1):1–46.

Heckman, J., Pinto, R., and Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, 103(6):2052–86.

Heckman, J. J. (1976). A life-cycle model of earnings, learning, and consumption. *Journal of Political Economy*, 84(4, Part 2):S9–S44.

Heckman, J. J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science*, 312(5782):1900–1902.

Heckman, J. J., LaLonde, R. J., and Smith, J. A. (1999). The economics and econometrics of active labor market programs. In *Handbook of labor economics*, volume 3, pages 1865–2097. Elsevier.

Heckman, J. J., Lochner, L., and Taber, C. (1998). Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of Economic Dynamics*, 1(1):1–58.

Heckman, J. J., Lochner, L. J., and Todd, P. E. (2006a). Earnings functions, rates of return and treatment effects: The mincer equation and beyond. *Handbook of the Economics of Education*, 1:307–458.

Heckman, J. J. and Masterov, D. V. (2007). The productivity argument for investing in young children.

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., and Yavitz, A. (2010b). The rate of return to the highscope perry preschool program. *Journal of Public Economics*, 94(1-2):114–128.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006b). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor economics*, 24(3):411–482.

Heller, S. B., Shah, A. K., Guryan, J., Ludwig, J., Mullainathan, S., and Pollack, H. A. (2017). Thinking, fast and slow? some field experiments to reduce crime and dropout in chicago. *The Quarterly Journal of Economics*, 132(1):1–54.

Hendren, N. and Sprung-Keyser, B. (2020). A unified welfare analysis of government policies. *The Quarterly Journal of Economics*, 135(3):1209–1318.

Hendricks, L. and Schoellman, T. (2018). Human capital and development accounting: New evidence from wage gains at migration. *The Quarterly Journal of Economics*, 133(2):665–700.

Hendricks, L. and Schoellman, T. (2023). Skilled labor productivity and cross-country income differences. *American Economic Journal: Macroeconomics*, 15(1):240–268.

Herkenhoff, K., Lise, J., Menzio, G., and Phillips, G. M. (2024). Production and learning in teams. Technical Report 2.

Hermo, S., Päällysaho, M., Seim, D., and Shapiro, J. M. (2022). Labor market returns and the evolution of cognitive skills: Theory and evidence. *The Quarterly Journal of Economics*, 137(4):2309–2361.

Hoekstra, M. (2009). The effect of attending the flagship state university on earnings: A discontinuity-based approach. *The Review of Economics and Statistics*, 91(4):717–724.

Hortaçsu, A., Luco, F., Puller, S. L., and Zhu, D. (2019). Does strategic ability affect efficiency? evidence from electricity markets. *American Economic Review*, 109(12):4302–4342.

Huggett, M., Ventura, G., and Yaron, A. (2006). Human capital and earnings distribution dynamics. *Journal of Monetary Economics*, 53(2):265–290.

Humphries, J. E. and Kosse, F. (2017). On the interpretation of non-cognitive skills–what is being measured and why it matters. *Journal of Economic Behavior & Organization*, 136:174–185.

Izadi, R. and Tuhkuri, J. (2021). Psychological traits and adaptation to the labor-market.

Izadi, R. and Tuhkuri, J. (2024). Evolving returns to personality.

Jackson, C. K. (2018). What do test scores miss? the importance of teacher effects on non–test score outcomes. *Journal of Political Economy*, 126(5):2072–2107.

Jackson, C. K., Porter, S. C., Easton, J. Q., Blanchard, A., and Kiguel, S. (2020). School effects on socioemotional development, school-based arrests, and educational attainment. *American Economic Review: Insights*, 2(4):491–508.

Jarosch, G., Oberfield, E., and Rossi-Hansberg, E. (2021). Learning from coworkers. *Econometrica*, 89(2):647–676.

Jedwab, R., Romer, P., Islam, A. M., and Samaniego, R. (2023). Human capital accumulation at work: Estimates for the world and implications for development. *American Economic Journal: Macroeconomics*, 15(3):191–223.

Johnson, R. C. and Jackson, C. K. (2019). Reducing inequality through dynamic complementarity: Evidence from head start and public school spending. *American Economic Journal: Economic Policy*, 11(4):310–49.

Jokela, M., Pekkarinen, T., Sarvimäki, M., Terviö, M., and Uusitalo, R. (2017). Secular rise in economically valuable personality traits. *Proceedings of the National Academy of Sciences*, 114(25):6527–6532.

Jones, B. F. (2014). The human capital stock: a generalized approach. *American Economic Review*, 104(11):3752–3777.

Kambourov, G. and Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1):63–115.

Kamenica, E. and Gentzkow, M. (2011). Bayesian persuasion. *American Economic Review*, 101(6):2590–2615.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., and Borghans, L. (2014). Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success. Technical report, National Bureau of Economic Research.

Kawano, L., Sacerdote, B., Skimmyhorn, W., and Stevens, M. (2024). On the determinants of young adult outcomes: Impacts of randomly assigned neighborhoods for children in military families. Technical report, National Bureau of Economic Research, Inc.

Khanna, G. (2023). Large-scale education reform in general equilibrium: Regression discontinuity evidence from india. *Journal of Political Economy*, 131(2):549–591.

Kim, T. (2021). Estimating pecuniary and non-pecuniary returns to college education for academically marginal students: Evidence from the college enrollment quota policy in south korea. *Economics of Education Review*, 83:102142.

Kinsler, J. and Pavan, R. (2015). The specificity of general human capital: Evidence from college major choice. *Journal of Labor Economics*, 33(4):933–972.

Kirkeboen, L. J., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111.

Klenow, P. J. and Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER macroeconomics annual*, 12:73–103.

Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H., and Falk, A. (2020). The formation of prosociality: causal evidence on the role of social environment. *Journal of Political Economy*, 128(2):434–467.

Kozakowski, W. (2023). Are four-year public colleges engines for economic mobility? evidence from statewide admissions thresholds.

Kredler, M. (2014). Experience vs. obsolescence: A vintage-human-capital model. *Journal of Economic Theory*, 150:709–739.

Krueger, D. and Kumar, K. B. (2004). Skill-specific rather than general education: a reason for us–europe growth differences? *Journal of Economic Growth*, 9:167–207.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, 117(5):914–940.

Lee, J.-W. and Lee, H. (2016). Human capital in the long run. *Journal of Development Economics*, 122:147–169.

Lemieux, T. (2006). The "mincer equation" thirty years after schooling, experience, and earnings. In *Jacob Mincer a pioneer of modern labor economics*, pages 127–145. Springer.

Lenard, M. A. and Silliman, M. (2024). Informal social interactions, academic achievement and behavior: Evidence from peers on the school bus. *Economic Journal*, forthcoming.

Levine, R. and Rubinstein, Y. (2017). Smart and illicit: who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, 132(2):963–1018.

Li, W., Duncan, G. J., Magnuson, K., Schindler, H. S., Yoshikawa, H., and Leak, J. (2020). Timing in early childhood education: How cognitive and achievement program impacts vary by starting age, program duration, and time since the end of the program. edworkingpaper no. 20-201. *Annenberg Institute for School Reform at Brown University*.

Lindenlaub, I. (2017). Sorting multidimensional types: Theory and application. *The Review of Economic Studies*, 84(2):718–789.

Lindner, A., Muraközy, B., Reizer, B., and Schreiner, R. (2022). Firm-level technological change and skill demand.

Lindqvist, E. and Vestman, R. (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the swedish enlistment. *American Economic Journal: Applied Economics*, 3(1):101–128.

Lise, J. and Postel-Vinay, F. (2020). Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, 110(8):2328–2376.

Lucas Jr, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1):3–42.

Ludwig, J. and Miller, D. L. (2007). Does head start improve children's life chances? evidence from a regression discontinuity design. *The Quarterly Journal of Economics*, 122(1):159–208.

Lyons, E. (2017). Team production in international labor markets: Experimental evidence from the field. *American Economic Journal: Applied Economics*, 9(3):70–104.

Ma, X., Nakab, A., and Vidart, D. (2024). Human capital investment and development: The role of on-the-job training. *Journal of Political Economy Macroeconomics*, 2(1):107–148.

Machin, S. and Van Reenen, J. (1998). Technology and changes in skill structure: evidence from seven oecd countries. *The Quarterly Journal of Economics*, 113(4):1215–1244.

Maćkowiak, B., Matějka, F., and Wiederholt, M. (2023). Rational inattention: A review. *Journal of Economic Literature*, 61(1):226–273.

Malamud, O., Pop-Eleches, C., and Urquiola, M. (2016). Interactions between family and school environments: Evidence on dynamic complementarities? Technical report, National Bureau of Economic Research.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2):407–437.

Manuelli, R. E. and Seshadri, A. (2014). Human capital and the wealth of nations. *American economic review*, 104(9):2736–2762.

Mbiti, I., Muralidharan, K., Romero, M., Schipper, Y., Manda, C., and Rajani, R. (2019). Inputs, incentives, and complementarities in education: Experimental evidence from tanzania. *The Quarterly Journal of Economics*, 134(3):1627–1673.

Mehmood, S., Naseer, S., and Chen, D. L. (2024). Altruism in governance: Insights from randomized training for pakistan's junior ministers. *Journal of Development Economics*, page 103317.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, 66(4):281–302.

Mincer, J. (1974). Schooling, experience, and earnings. human behavior & social institutions no. 2.

Mountjoy, J. (2024). Marginal returns to public universities. Technical report, National Bureau of Economic Research.

Neal, D. and Rosen, S. (2000). Theories of the distribution of earnings. *Handbook of income distribution*, 1:379–427.

Nelson, R. R. and Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *The American economic review*, 56(1/2):69–75.

Nores, M., Belfield, C. R., Barnett, W. S., and Schweinhart, L. (2005). Updating the economic impacts of the high/scope perry preschool program. *Educational Evaluation and Policy Analysis*, 27(3):245–261.

Öckert, B. (2010). What's the value of an acceptance letter? using admissions data to estimate the return to college. *Economics of Education Review*, 29(4):504–516.

OECD (2023). *Education at a Glance 2023*.

Oprea, R. (2020). What makes a rule complex? *American economic review*, 110(12):3913–3951.

Oreopoulos, P. (2006). Estimating average and local average treatment effects of education when compulsory schooling laws really matter. *American Economic Review*, 96(1):152–175.

Osman, A. and Speer, J. (2022). Are soft skills enough? experimental evidence on skill complementarity for college graduates. *Experimental Evidence on Skill Complementarity for College Graduates (August 1, 2022)*.

Ost, B., Pan, W., and Webber, D. (2018). The returns to college persistence for marginal students: Regression discontinuity evidence from university dismissal policies. *Journal of Labor Economics*, 36(3):779–805.

Papageorge, N. W., Ronda, V., and Zheng, Y. (2019). The economic value of breaking bad: Misbehavior, schooling and the labor market. Technical report, National Bureau of Economic Research.

Patrinos, H. A. and Psacharopoulos, G. (2020). Returns to education in developing countries. In *The Economics of education*, pages 53–64. Elsevier.

Pavan, R. (2011). Career choice and wage growth. *Journal of Labor Economics*, 29(3):549–587.

Petek, N. and Pope, N. G. (2023). The multidimensional impact of teachers on students. *Journal of Political Economy*, 131(4):1057–1107.

Psacharopoulos, G. and Patrinos, H. A. (2018). Returns to investment in education.

Rea, D. and Burton, T. (2020). New evidence on the heckman curve. *Journal of Economic Surveys*, 34(2):241–262.

Reyes, G. (2023). Cognitive endurance, talent selection, and the labor market returns to human capital. *arXiv preprint arXiv:2301.02575*.

Rosen, S. (1976). A theory of life earnings. *Journal of Political Economy*, 84(4, Part 2):S45–S67.

Rossi, F. (2020). Human capital and macroeconomic development: a review of the evidence. *The World Bank Research Observer*, 35(2):227–262.

Rossin-Slater, M. and Wüst, M. (2020). What is the added value of preschool for poor children? long-term and intergenerational impacts and interactions with an infant health intervention. *American Economic Journal: Applied Economics*, 12(3):255–286.

Sanders, C. and Taber, C. (2012). Life-cycle wage growth and heterogeneous human capital. *Annu. Rev. Econ.*, 4(1):399–425.

Schultz, T. W. (1961). Investment in human capital. *The American Economic Review*, 51(1):1–17.

Schunk, D., Berger, E. M., Hermes, H., Winkel, K., and Fehr, E. (2022). Teaching self-regulation. *Nature human behaviour*, 6(12):1680–1690.

Schweinhart, L. J., Barnes, H. V., and Weikhart, D. P. (2005). Significant benefits: The high/scope perry preschool study through age 27. *Child welfare: Major themes in health and social welfare*, 4:9–29.

Silliman, M. and Virtanen, H. (2022). Labor market returns to vocational secondary education. *American Economic Journal: Applied Economics*, 14(1):197–224.

Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics*, 50(3):665–690.

Smith, J., Goodman, J., and Hurwitz, M. (2020). The economic impact of access to public four-year colleges. Technical report, National Bureau of Economic Research.

Smith, M., Yagan, D., Zidar, O., and Zwick, E. (2019). Capitalists in the twenty-first century. *The Quarterly Journal of Economics*, 134(4):1675–1745.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1):65–94.

Song, J., Price, D. J., Guvenen, F., Bloom, N., and Von Wachter, T. (2019). Firming up inequality. *The Quarterly Journal of Economics*, 134(1):1–50.

Sorrenti, G., Zölitz, U., Ribeaud, D., and Eisner, M. (2024). The causal impact of socio-emotional skills training on educational success. *Review of Economic Studies*, page rdae018.

Spence, A. M. (1974). Job market signalling. *Quarterly Journal of Economics*, page 355–374.

Taber, C. and Vejlin, R. (2020). Estimation of a roy/search/compensating differential model of the labor market. *Econometrica*, 88(3):1031–1069.

Tinbergen, J. (1974). Substitution of graduate by other labour. *Kyklos: International Review for Social Sciences*.

Virtanen, H., Silliman, M., Kuuppelomäki, T., and Huttunen, K. (2024). Education, gender, and family formation.

Weidmann, B. and Deming, D. J. (2021). Team players: How social skills improve team performance. *Econometrica*, 89(6):2637–2657.

Weidmann, B., Vecci, J., Said, F., Deming, D. J., and Bhalotra, S. (2024). How do you find a good manager? *NBER WP Series*.

Welch, F. (1970). Education in production. *Journal of political economy*, 78(1):35–59.

West, M. R., Kraft, M. A., Finn, A. S., Martin, R. E., Duckworth, A. L., Gabrieli, C. F., and Gabrieli, J. D. (2016). Promise and paradox: Measuring students' non-cognitive skills and the impact of schooling. *Educational evaluation and policy analysis*, 38(1):148–170.

Zimmerman, S. D. (2014). The returns to college admission for academically marginal students. *Journal of Labor Economics*, 32(4):711–754.