

The Labor Market Value of Non-Cognitive Skills

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Abstract

In the last half-century, a large academic literature has emerged documenting the empirical relationship between non-cognitive skills and labor market outcomes. In this paper, I review this literature, putting emphasis on new work in economics. The literature provides overwhelming evidence that non-cognitive skills (e.g. internal locus of control, social skills, motivation, etc.) are associated with, and likely cause, labor market success. Furthermore, I summarize a growing literature that documents the rising value of non-cognitive skills relative to cognitive skills, especially post 2000, and that, due to the nature technological change, this trend is likely to continue. Finally, I document two shortcomings of the literature: (1) no study has successfully isolated the causal effect of non-cognitive skills training in a developed country and (2) very little is known about the value of signaling non-cognitive skills to employers.

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1 Introduction

In the last half-century, a large academic literature has emerged documenting the empirical relationship between non-cognitive skills¹ and labor market outcomes. In this chapter, I review this literature, putting emphasis on new work in economics. I also point out holes in the literature and suggest promising areas for future research.

There have been many reviews covering the economics of non-cognitive skills, so I find it important to highlight why mine is unique. First, this review is policy-oriented and intended for a wider audience than other recent reviews. Second, this review focuses on empirical research that links non-cognitive skills and labor market outcomes. And third, this review focuses on recent papers that have not been discussed in previous reviews. This review is complementary to [Heckman et al. \(2019\)](#), which covers more purely theoretical papers and research in psychology. Other excellent reviews that overlap with the material I cover include [Borghans et al. \(2008\)](#), [Almlund et al. \(2011\)](#), and [Kautz et al. \(2014\)](#).²

In section one of this review, I summarize the non-experimental literature on estimating the labor market value of non-cognitive skills, starting with the work of [Andrisani and Nestel \(1976\)](#). I conclude that, for a wide range of measurement techniques and skills, the overwhelming weight of the evidence supports the claim that non-cognitive skills significantly influence earnings and employment. I conclude this section by highlighting a recent and surprising discovery about how non-cognitive skills are related to economic outcomes studied in [Papageorge et al. \(2019\)](#). In this paper, the authors present evidence that “externalizing behavior” – a non-cognitive trait linked to aggression and childhood misbehavior – is both negatively associated with educational attainment and positively associated with wages. By illuminating the unexpected and context-specific nature of a particular non-cognitive skill, [Papageorge et al. \(2019\)](#) is a reminder of the need for more

¹I use the phrases *non-cognitive skills* and *character skills* interchangeably throughout this chapter. Following [Heckman et al. \(2014\)](#) and [Deming \(2017b\)](#), I use both terms to refer to skills that are not measured by standard cognitive and IQ assessments. My preferred term for these skills is character skills, but because non-cognitive is most common in the economics literature, I use it to limit confusion.

²I am indebted to the authors of each of these reviews because I have used them to find many of the sources I discuss.

nuanced analysis of these skills.

In section two, I discuss the experimental and quasi-experimental research on non-cognitive skills and labor market outcomes. This includes studying the adult labor market impacts of preschool, primary school, secondary school, and post-secondary training interventions that causally impacted participants' non-cognitive skills. Again, the vast majority of these studies suggest that improving non-cognitive skills increases employability and earnings potential. But, each of these interventions has a flaw: they impact many characteristics (e.g. cognitive skills, parental investment, etc.), so it is difficult to disentangle what proportion of their impact on labor market outcomes is through their impact on non-cognitive skills. Next I discuss the only four studies that overcome this problem. They each do so by experimentally evaluating the labor market effects of non-cognitive-skill-only job-training programs in four different developing countries – Jordan, Togo, India, and the Dominican Republic. The evidence from these studies generally indicates that improving non-cognitive skill positively impacts wages and employment, but the results are mixed. This highlights the need for more research that isolates the impact of non-cognitive skills training on labor market outcomes, especially in the US.

In section three, I document changes in the relative employer demand of non-cognitive and cognitive skills over the last three decades. First, I discuss the evidence that the emergence of computer technology has shifted the types of tasks humans are employed to do away from cognitive routine tasks toward tasks that require more flexibility. Second, I present the hypothesis that non-cognitive skills are more difficult to replace with machine labor because they are difficult to model algorithmically. Third, I summarize evidence that, consistent with this hypothesis, non-cognitive skills have become relatively more valuable within most occupations and the occupations that require high levels of non-cognitive skills are simultaneously becoming more prevalent. I conclude this section by suggesting that, based on recent work by [Webb \(2019\)](#) and [Autor and Salomons \(2019\)](#), this trend is likely to continue.

In section four, I point out a major shortcoming in the academic literature: there are no published studies that estimate the effect of revealing these skills to employers. Even worse, there is

no set taxonomy of non-cognitive skills, meaning that how workers should communicate these skills is also an open question. On this, I discuss [Piopiunik et al. \(2020\)](#) and [Bassi and Nansamba \(2019\)](#), two working papers that analyze experiments (in Germany and Uganda, respectively) that both find that employers care about non-cognitive skills in hiring. These studies suggest that there may be large efficiency gains to lowering the cost of signaling non-cognitive skills to employers in both advanced and developing economies. I conclude this section by discussing how new skill-measurement technologies and online job-matching platforms can tell us about which non-cognitive skills employers care about, which industries and occupations care about which skills, and what is the best way to display these skills so that recruiters notice.

2 Non-Experimental Evidence

Though one can find hints dating back to the work of Adam Smith ([Spengler 1977](#)), theorizing about the labor market value of skills other than traditional cognitive measures formally started in [Roy \(1951\)](#). In this paper, Roy argues that wage differentials between occupations are not just arbitrage opportunities, but instead are caused by unobserved differences in characteristics of the workers across occupations. Echoing this idea, [Bowles and Gintis \(1976\)](#) argue that education provides students with “employer-valued attributes” such as punctuality and hard work, which might explain some portion of the economic return to education.

Empirical work using applied econometrics to identify which non-cognitive characteristics affect labor market outcomes started in the mid 70s with three studies: [Edwards \(1976\)](#), [Andrisani and Nestel \(1976\)](#), and [Andrisani \(1977\)](#). In the first of these studies, [Edwards \(1976\)](#) analyzed data on a sample of 455 (mostly government) workers to test the hypothesis, laid out in [Bowles and Gintis \(1976\)](#), that employers reward certain attributes, such as willingness to follow rules, dependability, and internalization of firm values. Using peer ratings of each worker on these three dimensions, the author finds that each of these non-cognitive skills is associated with higher wages, conditional on educational attainment, socioeconomic background, and cognitive ability. In the

other two studies, [Andrisani and Nestel \(1976\)](#) and [Andrisani \(1977\)](#) use regression analysis on data from the National Longitudinal Survey (NLS) and both find that, holding educational attainment constant, a higher level of *internal* locus of control³ is associated with higher wages and annual earnings, higher levels of occupational attainment,⁴ and higher rates of job satisfaction.

These initial papers sparked an explosion of work in the following decades that all had the same structure: find a measure of non-cognitive skills of a population (usually in survey data) and estimate regressions of labor market characteristics on those skills conditioning on observables such as education, demographics, and family background. Using this strategy, papers have found that self-esteem ([Goldsmith et al. 1997](#); [Murnane et al. 2001](#)), orientation towards challenge ([Dunifon and Duncan 1998](#)), personal control ([Dunifon and Duncan 1998](#)), leadership skills ([Kuhn and Weinberger 2005](#)), and motivation to work ([Segal 2012](#)) are positively associated with wages, while personal efficacy⁵ ([Duncan and Morgan 1981](#)), childhood aggression ([Groves 2005](#)), childhood withdrawal ([Groves 2005](#)), and in-school misbehavior ([Segal 2013](#)) are all negatively associated with wages. The magnitudes of the coefficients across these studies vary widely, ranging from a 15% increase in wages associated with a one standard deviation increase in personal control ([Dunifon and Duncan 1998](#)) to a 3% increase in wages associated with a one standard deviation decrease in childhood withdrawal ([Groves 2005](#)).⁶

A few papers in this category explore bundles of non-cognitive skills, such as the work of Peter Mueser (reported in [Jencks et al. \(1979\)](#)), who finds that social sensitivity, impulsiveness, culture, maturity, leadership, executive ability, industriousness, and perseverance are jointly associated with occupational status; [Filer \(1980\)](#), who finds that sociability, friendliness, and thoughtfulness are all

³Locus of control measures whether an individual believes that they are in control of their outcomes or not. Those with high internal locus of control believe that they can impact outcomes in their lives while those with low internal (or high external) locus of control believe that their outcomes are out of their hands and caused by the external world. In these papers, the authors use Rotter's Internal-External Control Scale, which is a score elicited via a multi-item survey ([Rotter 1966](#)).

⁴Specifically, the authors measured Duncan's Socio-Economic Index, which is an index of income and educational attainment associated with an occupation ([Duncan 1961](#)). For the remainder of this review, each mention of "occupational attainment" refers to the same measure.

⁵This is an alternative measure of external locus of control.

⁶I use normalized regression coefficients from these studies, most of which were collected in Table A2 of [Lindqvist and Vestman \(2011\)](#).

associated with higher earnings; and [Heckman et al. \(2006\)](#), who finds that an index combining a measure of self-esteem and internal locus of control is positively associated with higher earnings for males and females.

In addition to the regression estimates discussed above, [Heckman et al. \(2006\)](#) is one of a series of papers that combine economic theory and econometrics (aka structural estimation) to understand the returns to non-cognitive skills (e.g. [Willis and Rosen 1979](#); [Cunha and Heckman 2007](#); [Cunha et al. 2010](#)). Explaining the empirical methods used in these papers is beyond the scope of this review, but their findings have been too influential to ignore. I see three main takeaways from this body of work: (1) non-cognitive skills and cognitive skills likely explain similar amounts of the variation in earnings, (2) non-cognitive and cognitive skills are complimentary in producing labor market success, and (3) non-cognitive and cognitive skills help produce one another, which creates diminishing returns to investment in either type of skill over the life-cycle.⁷

Consistent with the general findings in the non-cognitive skill literature, a related literature on the General Educational Development (GED) credential has developed. This work establishes that the return to the GED is lower than the return to high school graduation ([Heckman and LaFontaine 2006](#)), that GED test takers have lower non-cognitive skills ([Heckman and Rubinstein 2001](#)),⁸ and that this non-cognitive skill difference is a significant driver of the gap in earnings and employment between GED test takers and high school graduates ([Heckman et al. 2011a, 2014](#)).

There are two papers, [Lindqvist and Vestman \(2011\)](#) and [Papageorge et al. \(2019\)](#), that I consider to be at the frontier of this type of research, so I will discuss each of them in detail. [Lindqvist and Vestman \(2011\)](#) exploit detailed data from the Swedish military registry; unlike the US, Sweden has mandatory military service for men, so these data contain the near universe of men. Over the course of two days, each enlistee is assessed on both cognitive and non-cognitive skills. For cognitive skills, each enlistee takes a four part test with 40 questions in each part. Performance

⁷It is important to note that the idea that returns to investment in human capital (especially in non-cognitive skills) decreases in age has been contested by economists. For example, [Hendren and Sprung-Keyser \(2019\)](#) perform a comprehensive evaluation of the return on investment from various government policies and find little evidence that the return to educational interventions depend on the age of the children who receive them.

⁸In [Heckman and Rubinstein \(2001\)](#), non-cognitive skills are proxied for by misbehavior, illicit drug use, and criminal activity.

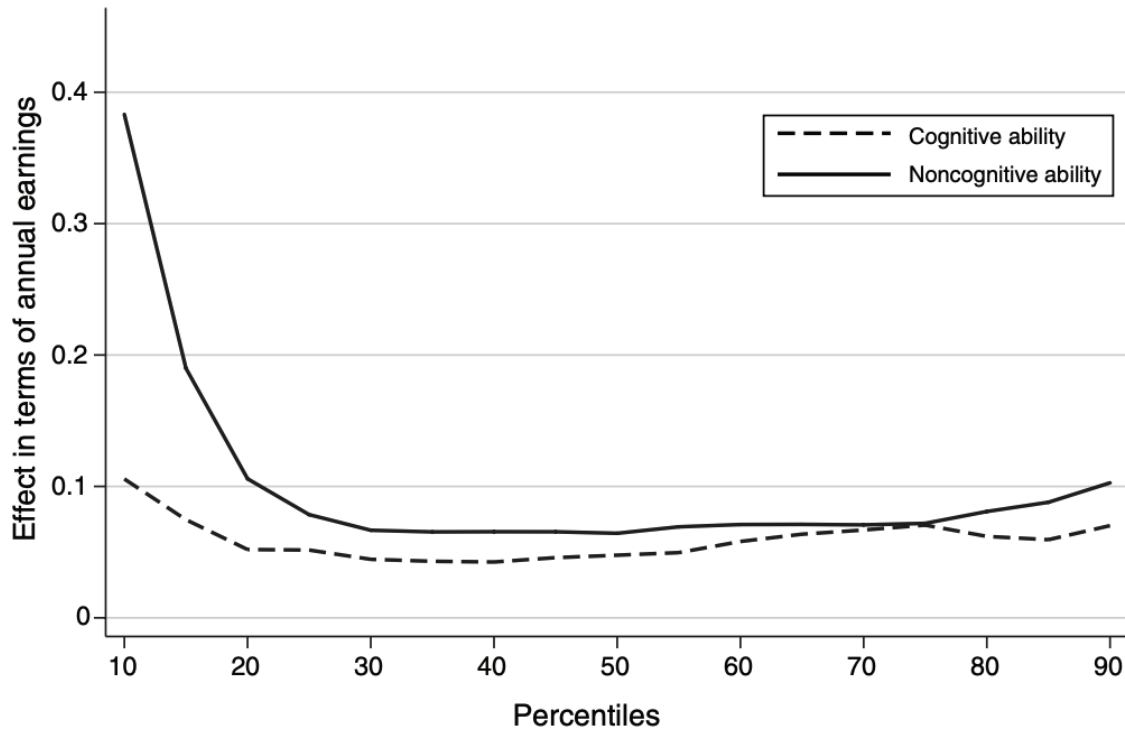
in each part is aggregated into a single score from 1 (lowest) and 9 (highest). For non-cognitive skills, a trained psychologist interviews each enlistee and judges their willingness to assume responsibility, independence, outgoing character, initiative, persistence, social skills, and emotional stability. These judgments are aggregated into a final score from 1 to 9 as well. The authors link this information to a representative sample of the Swedish population (LINDA) that contain labor market outcomes such as employment and wages.

The authors argue that the way in which non-cognitive skills are measured in their data is superior because in-person interviews give certified psychologists access to more extensive information about each enlistee, which makes the overall measure of non-cognitive skills more precise than in previous papers. Furthermore, this improvement on precision may be partially caused by misreporting and inattention on non-cognitive surveys, which is the primary method that past studies have used to extract non-cognitive capabilities.

Following past studies, the authors estimate linear regressions of labor market outcomes (i.e. wages, unemployment, and annual earnings) on indices of non-cognitive and cognitive skills controlling for region of residence, cohort, family background, enlistment into military service, and educational attainment. From these regressions the authors find that a one standard deviation increase in cognitive skill (non-cognitive skill) is associated with roughly a 5% (8%) increase in wages, a 2 (3) percentage point decrease in one's likelihood of being unemployed, and a 10% (11%) increase in annual earnings. Thus, both types of skill matter for all three dimensions of labor market success and, if anything, non-cognitive skills matter slightly more.

The main reason that I consider [Lindqvist and Vestman \(2011\)](#) to be at the frontier of non-experimental studies of the return to non-cognitive skills is that the size of their sample (just over 14,000 men) gives them the ability to analyze the return to non-cognitive and cognitive skills at different parts of the distributions of skill and earnings. For example, the authors estimate that at the tenth percentile of the earnings distribution, an increase in non-cognitive skill by one standard deviation is associated with almost a 40 percent increase in annual earnings, whereas an increase in cognitive skill at this level is only associated with a 11 percent increase in earnings (see Figure

Figure 1: Effect of Cognitive and Noncognitive Skills on the Earnings Distribution (Sweden)
Lindqvist and Vestman (2011)



Notes: This is Figure 3 from [Lindqvist and Vestman \(2011\)](#). Following the methodology of [Firpo et al. \(2009\)](#), it plots results from a quantile regressions of earnings on indices of cognitive and non-cognitive skills, controlling for a quadratic in potential post-education experience and dummy variables for secondary school, two years post-secondary schooling, university degree and a PhD. The y-axis should be interpreted as percentage change, as the authors plot the effect in absolute terms divided by average annual earnings at the respective quantile.

1). Furthermore, they find both that the (negative) effect of non-cognitive skill on poverty has the greatest magnitude for those with low levels of cognitive skill. Together, this suggests that the returns to non-cognitive skills may be the most useful for those who have the lowest labor market opportunities.

The other frontier (working) paper, [Papageorge et al. \(2019\)](#), explores the returns to two types of childhood misbehavior: internalizing and externalizing. Internalizing behavior, the authors explain, is related anxiety, depression, shyness, unassertiveness, and fearfulness, while externalizing behavior is related to aggression and hyperactivity. This paper challenges the conventional wisdom that all misbehavior in school is indicative of underlying deficiencies in non-cognitive skill that hurt both school and labor market performance (e.g. [Segal 2013](#)). Instead, the authors present evidence that externalizing behavior, while detrimental to school performance, is actually demanded and

rewarded in the labor market.

To explore this, the authors run regression analyses of educational attainment (years of education) and weekly earnings on normalized measures of childhood levels of externalizing behavior and internalizing behavior as well as controls for family background and demographics.⁹ The authors conduct this analysis across five frequently used datasets: the National Child Development Survey (NCDS), the British Cohort Study (BCS), the National Education Longitudinal Survey (NELS), the Panel Study of Income Dynamics, and the National Longitudinal Survey of Youth (NLSY).

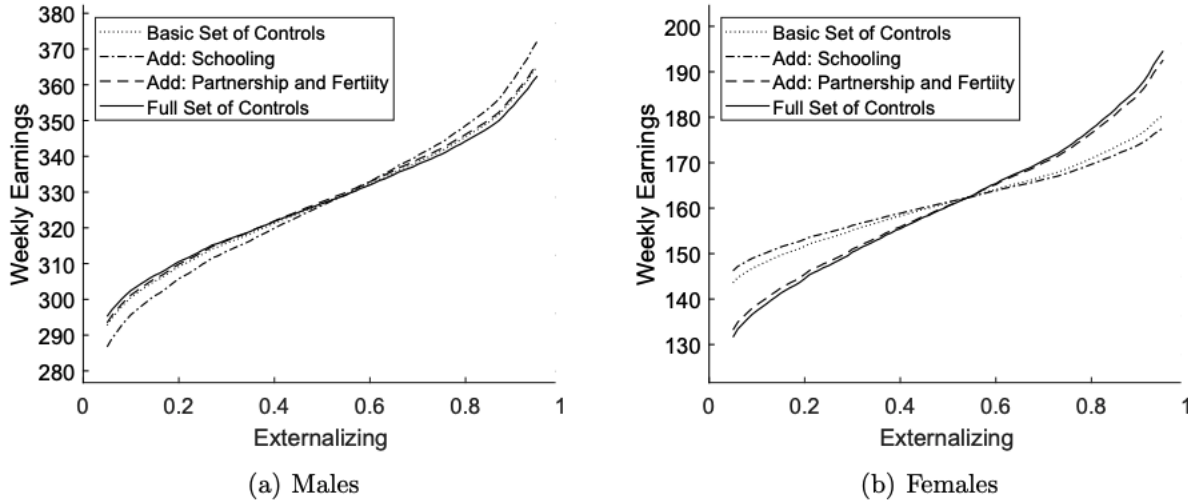
The authors find overwhelming evidence that, while both externalizing and internalizing behavior reduce educational attainment, externalizing behavior seems to increase earnings. Specifically, the effect of a one standard deviation increase in childhood externalizing behavior results in a .07–.17 decrease in years of schooling and a .2%–7% increase in earnings across all five data sets. In contrast, a one standard deviation increase in childhood internalizing behavior is also associated with a .07–.17 decrease in years of schooling but a 3%–9% decrease in earnings. Additionally, they find that the positive effects of externalizing behavior on earnings is driven by those who did not grow up in poverty.

I consider [Papageorge et al. \(2019\)](#) to be at the frontier for two reasons: it explores a more nuanced theory of how particular types of non-cognitive skills impact outcomes and it makes use of a wide range of data sources across countries. [Papageorge et al. \(2019\)](#) demonstrate that more than four decades since the first non-experimental empirical analysis of the labor market value of non-cognitive skills, there still remain interesting and policy-relevant research questions that can be answered using these methods.

As a whole, this literature overwhelmingly finds that non-cognitive skills are significantly associated with wages, earnings, employment, and occupational attainment. A weakness of this literature – and of most social science – is that novelty tends to be rewarded over nuance, so the set of non-cognitive skills examined is sprawling. There are more one-off papers that examine a

⁹Though beyond the scope of this review, the authors also estimate a structural model using simulated maximum likelihood estimation and find results consistent with the regression analyses I discuss.

Figure 2: Decomposition of Effects of Externalizing on Weekly Earnings
Papageorge et al. (2019)



Notes: This is adapted from Figure 1 of [Papageorge et al. \(2019\)](#). This figure visualizes the results from regressing weekly earnings on a varying set of controls. It illustrates how the predicted weekly earnings in regression models with different sets of controls vary, when we increase externalizing behavior from the lowest 5th percentile to the highest 95th percentile, keeping other latent skills and covariates at the population median.

“new” skill instead of replications or elaborations of past research. This is problematic because it means some of the findings are likely non-robust or incomplete. For example, [Papageorge et al. \(2019\)](#) partially overturn prior evidence that students who are prone to misbehave in school also lack highly valued non-cognitive skills.¹⁰ Still, certain skills – such as a sense of control, motivation, and self-esteem – are partially correlated with wages in a consistent way across studies, which is highly suggestive that cultivating these skills improves one’s labor market outcomes.

3 Causal Evidence

The literature discussed in the previous section is suggestive, but does not establish a causal link between non-cognitive skills and labor market success. This is because associations between labor market outcomes and non-cognitive skills may be driven by omitted variable bias. For example, people with high internal locus of control may tend to receive high quality education, causing

¹⁰Also, that [Papageorge et al. \(2019\)](#) is currently being revised for the *Journal of Political Economy* (a top 5 economics journal) suggests that meticulous research that adds nuance to our current understanding of how non-cognitive skills are valued in the labor market can gain academic acceptance.

them to earn more and experience less unemployment than those with low levels of internal locus of control. In this case, partial correlations between these labor market outcomes and non-cognitive skills would not measure the causal effect of cultivating non-cognitive skills, and thus would not be useful for informing policy.

To overcome these issues, many studies resort to using experiments (aka randomized evaluations) or natural experiments (aka quasi-experiments) to establish a causal link between non-cognitive skills and labor market outcomes. In this setting, an experiment is an evaluation that consists of randomly assigning participants to a “treatment” (e.g. a job-training program) that improves non-cognitive skill and comparing their labor market outcomes to the set of participants who did not receive the treatment. A natural experiment, on the other hand, takes advantage of an event that occurred in the real world that as-good-as-randomly exposed some people to a treatment; this allows the researcher to compare those who happened get “treated” to those happened to go “untreated”, approximating an experimental comparison. Though there are no published randomized experiments (to my knowledge) that isolate the labor market impact of improving non-cognitive skills in the US, there are many (quasi) experimental studies that examine the effect of interventions that simultaneously impact non-cognitive skill and other factors. Though imperfect, some of this evidence is highly suggestive.¹¹

One of the most prominent of these randomized interventions was the Perry Preschool Program (PPP). The program, administered in Ypsilanti, Michigan in the early-1960’s, offered high-quality preschool for two years to a randomly selected¹² set of low-IQ and low-income black children from ages 3 to 4. Long-term comparisons between the treated and control group from this study show that PPP caused increases in earnings, employment, educational attainment and decreases in crim-

¹¹In this section, I limit myself to studies that explicitly link (quasi) randomly induced changes in non-cognitive skill to concrete labor market outcomes. This excludes the growing literature evaluating different educational programs – such as PATHS (Bierman et al. 2010), Tools of the Mind (Barnett et al. 2008), and EPIS (Martins 2017) – designed to change non-cognitive skills. It also excludes educational interventions for which short-term or long-term effects have been studied, but detailed measures of non-cognitive skills are unavailable – such as Head Start (Deming 2009; Bailey et al. 2018). For an overview of the broader literature on education and non-cognitive skills, I refer readers to Heckman and Kautz (2014), Heckman et al. (2014), and Heckman et al. (2019).

¹²There is some evidence that randomization of PPP was imperfect, but the results on these outcomes are robust to corrections for this. For a more complete discussion of this, see Heckman et al. (2011b).

inality, despite having had no lasting impact on cognitive ability¹³ (Cunha et al. 2006; Heckman et al. 2010).¹⁴ For a plot of the IQ differences in the treatment and control group depicting fade out of the cognitive skill impacts of PPP, see Figure 3. Furthermore, Heckman et al. (2013) show that PPP did have short-term impacts on externalizing behavior and academic motivation (see Figure 4). Taken together, these findings indicate that PPP most likely impacted employment and earnings later in life by improving non-cognitive skills. To explore this, Heckman et al. (2013) conduct a mediation analysis and conclude that more than 20% of PPP long-term impact on monthly income (measured at age 27) and employment (measured at age 40) can be attributed to non-cognitive skill improvements of the treated group.¹⁵ Despite these efforts, it is ultimately impossible to rule out that the long-term impacts of PPP came through other channels, such as improved parenting or social networks (both of which are likely correlated with non-cognitive skill). But, the full set of evidence on PPP¹⁶ strongly supports a causal link between non-cognitive skill and labor market outcomes.

Often compared with PPP, the Abecedarian Programme (ABC) is another preschool program that, based on a randomized evaluation, appears to have impacted non-cognitive skills. ABC was an intensive preschool intervention that enrolled students as young as 6-weeks old and lasted through third grade. Like PPP, ABC had positive impacts on later adult outcomes, such as health and employment, and non-cognitive skills, such as childhood aggression (Conti et al. 2016). But, it is more difficult to separate out the contribution of non-cognitive skills to changes in adult outcomes

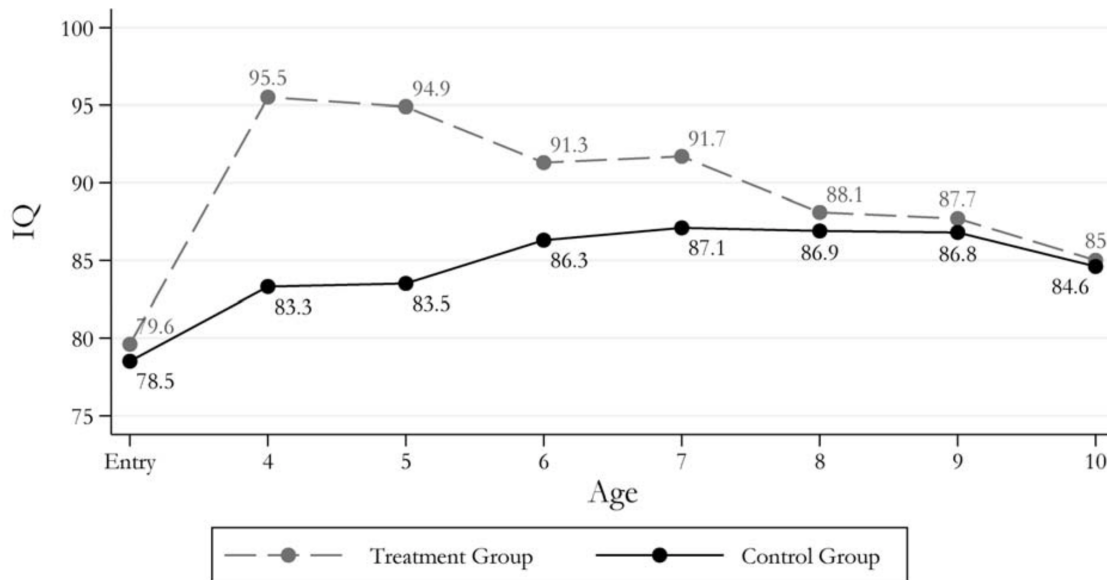
¹³It is important to note that the effect of PPP on cognitive ability varies slightly for males and females. For males, the average IQ in the treatment group is actually 2.3 points lower than the control group by age 10 and the difference is statistically insignificant. For females, the average IQ in the treatment group is 5 points higher than the control group by age 10 and the difference is marginally significant.

¹⁴Together, Heckman et al. (2010) demonstrates that the rate of return of PPP was between 7%-10%, and Hendren and Sprung-Keyser (2019) estimate that PPP has a marginal value of public funds of roughly \$44, meaning that beneficiaries would have been willing to pay 44 dollars per dollar investment in PPP.

¹⁵The majority of the earnings impacts come through reductions in externalizing behavior, which appears to contradict the findings of Papageorge et al. (2019). Papageorge et al. (2019) resolve this by pointing out that the PPP sample are low Socio-Economic Status and the impact of externalizing on earnings may vary by earnings and demographics. In fact, Papageorge et al. (2019) find that in a low-SES subsample of the British Cohort Study (their primary data) the positive association of externalizing behavior with earnings disappears.

¹⁶Though the effects of PPP on IQ, educational attainment, employment, earnings, and criminality have been studied in many researchers (Barnett 1985, 1996; Rolnick and Grunewald 2003; Belfield et al. 2006), the findings I summarize in this review are taken from Heckman et al. (2010), and Heckman et al. (2013) because they address (or are at least cognizant of) issues due to small sample size, sensitivity, and imperfect randomization.

Figure 3: Fadeout of Cognitive Impacts of the Perry Preschool Program
Almlund et al. (2011)



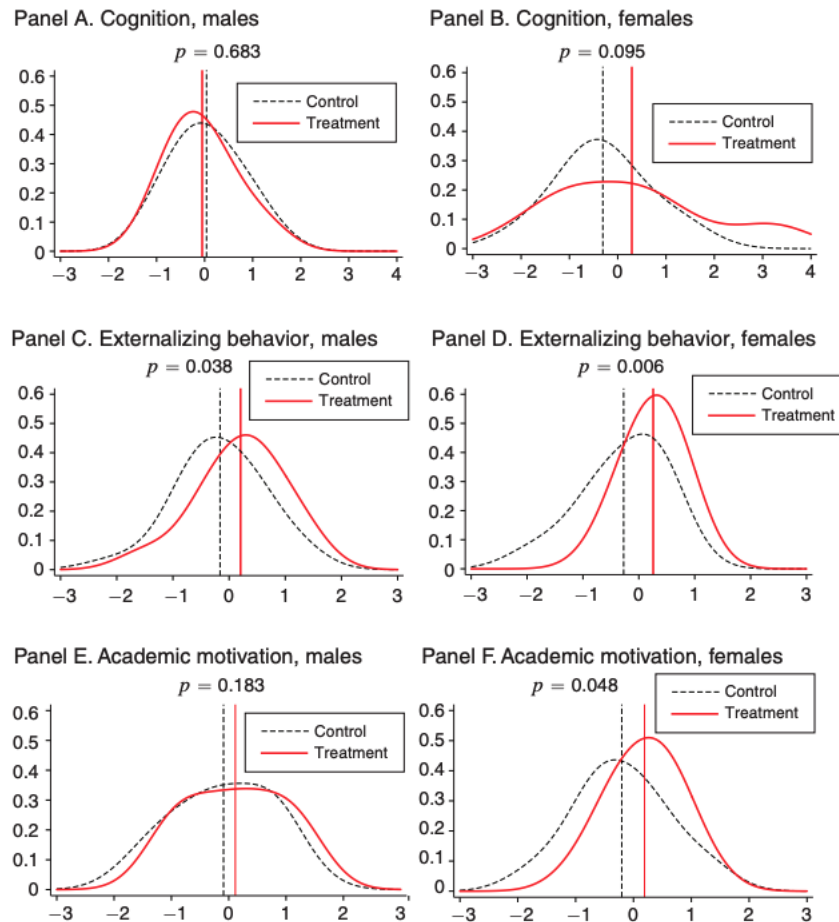
Notes: This is Figure 1 from [Almlund et al. \(2011\)](#). It can also be found in [Cunha et al. \(2006\)](#) and [Heckman and Masterov \(2007\)](#). IQ was measured on the Stanford-Binet Intelligence Scale ([Terman and Merrill 1960](#)). Test was administered at program entry and each of the ages indicated.

because the program also had a lasting impact on cognitive skills ([Kautz et al. 2014](#)).

The final notable preschool program is the Chicago Child-Parent Center (CPC). CPC is a large-scale preschool program, serving mainly low-income black families, that provides reading, writing, and math training as well as parenting instruction. The effects of this program have been evaluated using a matched sample design, whereby the authors compared outcomes between kids who attended CPC to similar kids who attended a different preschool ([Reynolds et al. 2011a,b](#)). These studies find that kids who attended CPC show higher social and emotional competence by age 13 and earn higher income at age 28. Unlike PPP and ABC, however, cognitive skills were not directly measured, so it is difficult to know what proportion of the earnings gain we should attribute to non-cognitive skill improvement.

Two similar programs show evidence that non-cognitive skills can be shaped during elementary school: (1) the Seattle Social Development Project (SSDP) and (2) the Montreal Longitudinal Experimental Study (MLES). Both SSDP and MLES were elementary school programs that provided training that was intended to strengthen relationships between teachers, parents, and school

Figure 4: Perry Preschool Impacts on Non-Cognitive Skills
Heckman et al. (2013)



Notes: This is Figure 5 from Heckman et al. (2013). It depicts probability density functions of factor scores. Numbers above the charts are one-sided p-values testing the equality of factor score means for the treatment and control groups. Higher externalizing behavior corresponds to more socially desirable behavior.

students. Both programs also focused on fostering behavioral skills like conflict resolution and social skills. Like CPC, evaluations of these programs have found that students enrolled had higher non-cognitive skills (i.e. self-efficacy or social skills) during young adulthood and higher earnings or unemployment in their mid 20s (Durlak et al. 2011; Algan et al. 2014). But, also like CPC, cognitive skills were not directly measured, so it is difficult to figure out the mechanism through which earnings increased. One distinguishing feature of SSDP is that the program showed no effect on any test scores, which suggests that cognitive skills likely were not impacted, strengthening the argument that positive labor market outcomes were caused by non-cognitive skill improvements.

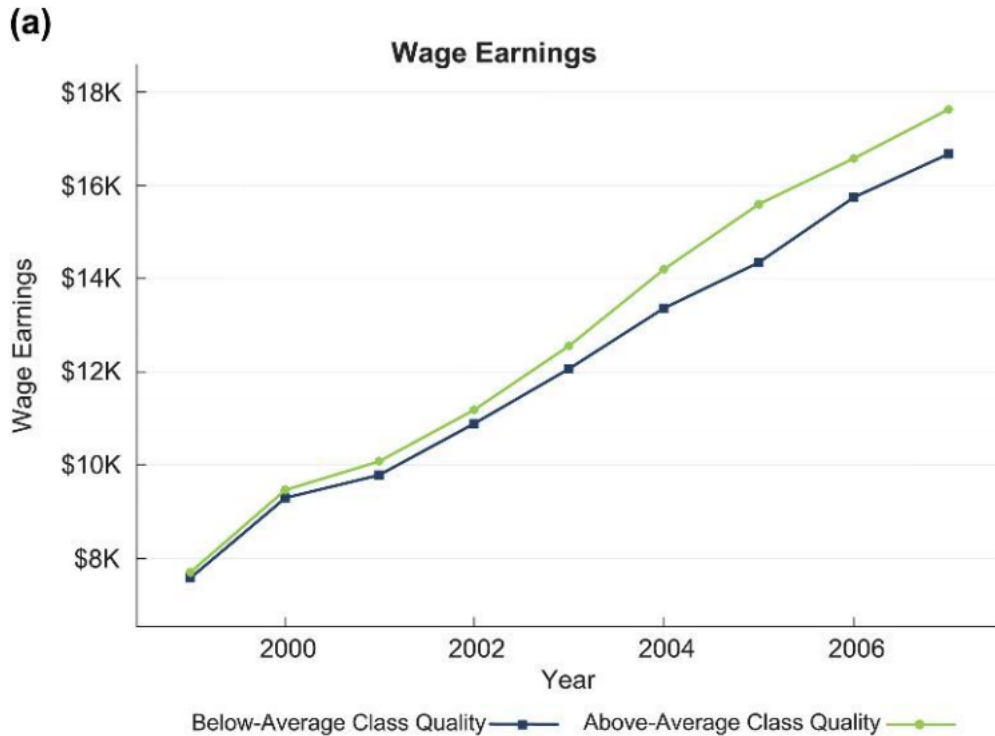
One obvious place where kids learn non-cognitive skills is in school and evaluations of the Student/Teacher Achievement Ratio (STAR) experiment provide insight into what classroom characteristics facilitate this type of development. Project STAR randomized 11,571 students into different elementary school classes from kindergarten through third grade (henceforth abbreviated K-3). Importantly, classes differed along various dimensions, such as by size, teacher characteristics, and peer characteristics, giving researchers the opportunity to examine the causal effect of these three factors on school achievement, skill development, and adult outcomes. In their long-term analysis of STAR, [Chetty et al. \(2011\)](#) find that kindergarten class quality, proxied for by average classmate test scores, has a statistically significant positive impact on both test scores and earnings; students assigned to a class with quality one standard deviation above the mean score roughly 9 percentiles higher on K-3 test scores and earn 3% more at age 27 (see Figure 5). The test score impacts, however, fade out by 8th grade, making it unlikely that the earnings gains can be explained by cognitive skill improvements alone (see Figure 6). The authors argue that non-cognitive skill improvements, then, likely drive a sizable portion of the effect. Consistent with this hypothesis, effects on effort, initiative, and lack of disruptive behavior persist through 8th grade.

Related to these findings, [Jackson \(2018\)](#) compares the long-term effect of being assigned to test-score-improving teachers versus behavior-improving teachers. In the nomenclature of the education literature, the former have high test score Teacher Value Added (TVA) and the latter have high non-cognitive TVA. To perform this analysis, [Jackson \(2018\)](#) uses data that include all ninth-grade students and their teachers in North Carolina public schools from 2005 to 2012. First, [Jackson \(2018\)](#) uses regression analysis to estimate TVA scores for individual teachers on both test score and non-cognitive dimensions.¹⁷ The author then estimates the partial correlation between non-cognitive TVA and test score TVA of ninth-grade teachers with later life outcomes of their students.¹⁸ From this analysis, the author reports two main findings: (1) teachers' test score

¹⁷The non-cognitive skill index is derived from the number of ninth grade absences, whether the student was suspended during ninth grade, ninth-grade GPA, and whether the student enrolled in tenth grade on time. It is important to note that GPA is a function of cognitive and non-cognitive skills, which suggests that this measure does not isolate non-cognitive skills perfectly.

¹⁸Though [Jackson \(2018\)](#) does not use quasi-random or random assignment to identify effects of teachers, it uses more sophisticated methods and robustness checks than almost all of the papers mentioned in Section 1. Furthermore,

Figure 5: Impacts of Class Quality on Adult Wage Earnings
Chetty et al. (2011)



Notes: This is panel (a) of Figure 5 from [Chetty et al. \(2011\)](#). This figure shows mean wage earnings by year (from ages 19 to 27) for students in two groups of classes: those that were above the class quality median and those that were below. Class quality is defined as the difference between the mean end-of-entry-grade test scores of a student's classmates and (grade-specific) schoolmates.

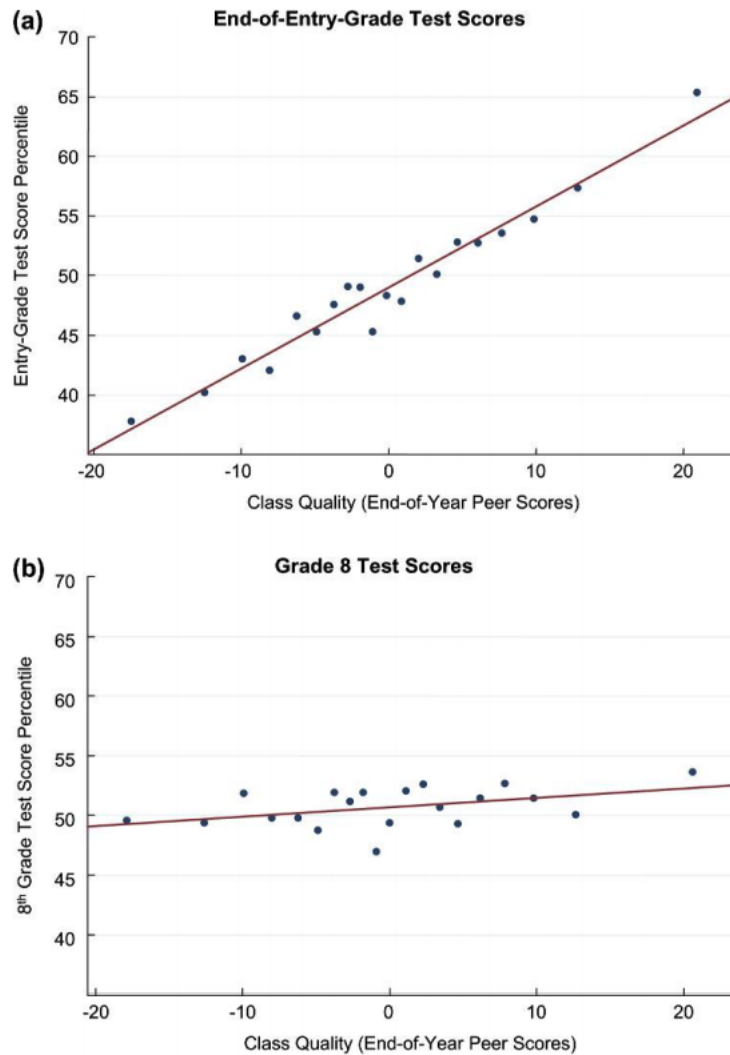
TVA is weakly correlated with their non-cognitive TVA and (2) teachers with high non-cognitive TVA improve long-run outcomes more than teachers with high test score TVA. [Jackson \(2018\)](#) calculates that, through the effect on high school graduation, having a teacher that is one standard deviation above the mean on non-cognitive TVA increases annual earnings by roughly \$160 per year per student.¹⁹

Another source of causal evidence on the value of non-cognitive skills comes from evaluations of job-training programs such as Job Corps, the National Guard ChalleNge, Career Academies, and, most recently, Year Up. The oldest of the four programs is JC, which was started in the early

it attempts to estimate the effect of something that changes non-cognitive vs. cognitive skill, on long term outcomes, instead of correlating levels of non-cognitive and cognitive skill with labor market outcomes. For these reasons, I felt it fit in this section despite its lack of experimental design.

¹⁹It is important to note that Jackson (2018) does not link students to labor market outcomes directly, but instead does a back-of the envelope calculation using the return to high school graduation calculated by the Bureau of Labor Statistics.

Figure 6: Fadeout of Test Score Impacts of Class Quality
Chetty et al. (2011)



Notes: This is Figure 4 from [Chetty et al. \(2011\)](#). The x axis in all panels is class quality, defined as the difference between the mean end-of-entry-grade test scores of a student's classmates and (grade-specific) schoolmates. The dependent variable in panel (a) is the student's own test score at the end of the grade in which he entered STAR. The coefficient of end-of-entry-grade test scores on class quality is 0.68 (s.e. = 0.03), implying that a 1 percentile improvement in class quality is associated with a 0.68 percentile improvement in test scores. The dependent variable in panel (b) is a student's test score at the end of 8th grade. The coefficient of 8th grade test scores on class quality is 0.08 (s.e. = 0.03).

1960's. In Job Corps, youth spend one year getting job-specific training, remedial education, and social skills training. Though early analysis via randomized experiment showed increases in wages and decreases in welfare dependence ([Mallar et al. 1982](#)), longer-term follow ups using tax records have found that these results fade over time ([Schochet et al. 2008](#)). The National Guard Challenge is a program that was started in the early 1990's that targets high school dropouts and gives them

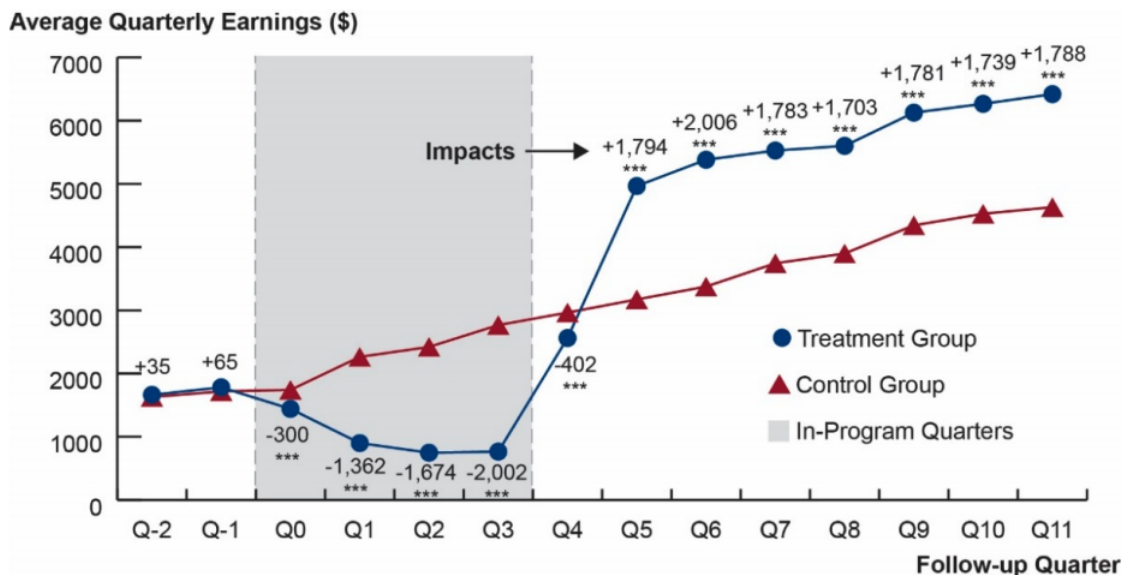
comprehensive training and remediation in a military base. Like Job Corps, this program had short-term employment and earnings impacts in the first three years, but a longer-term follow up has yet to be conducted (Bloom et al. 2009). Career Academies work within high schools and provide students with occupation-specific training, much like an apprenticeship. A randomized evaluation of Career Academies studied in Kemple and Willner (2008) finds impacts on male earnings, but no effects on educational outcomes. Furthermore, treated males are less likely to live with their parents and are more likely to be married or to live with their children, all of which suggests that they experienced cognitive skill improvement.²⁰

The last job-training program I will mention is Year Up (YU). YU started in the early 2000s and offers 18-24 year olds without college degrees a one-year immersive job training experience. YU offers technical skill training that teaches specific software and computer skills. What sets YU apart, however, is its explicit focus on developing participants' "professional" skills (i.e. dressing appropriately, being on time, and workplace communication). YU not only teaches these skills, but also penalizes participants by reducing their stipend if they fail to be professional along some dimension. This forces participants to learn professional skills and build habits. Finally, YU matches participants to internships, where they learn on the job skills for about six months.

Two randomized evaluations have found large short-term impacts of YU on earnings (Roder and Elliott 2014; Fein and Hamadyk 2018). The former study finds yearly earnings gains of about \$1,410 and the latter study finds yearly earnings gains of roughly \$2,285 (see Figure 7), which is larger in magnitude to other job-training programs. Another distinguishing feature of YU is that the earnings gains are driven almost completely by increases in both wages and the proportion working full-time (as opposed to part-time). This suggests that the gains may be driven by productivity capital gains, and because of the non-cognitive focus, it is reasonable to conclude that these skills contribute. But, because YU is such a comprehensive program, it is very difficult to know the extent to which non-cognitive skills contribute to its effects. It is also important to note that long-

²⁰A related program is the Canadian Self-Sufficiency Project, which was a study that randomly hired a subset of welfare enrollees and found that working had a positive effect on Internal Locus of Control (Gottschalk 2005). This suggests that working can increase non-cognitive skill, which suggests that employment requires these skills.

Figure 7: Three-Year Impacts of Year Up
Fein and Hamadyk (2018)



Notes: This is Exhibit ES 3 from [Fein and Hamadyk \(2018\)](#). Impacts appear as numbers giving differences in average earnings for treatment and control group members in each follow-up quarter. Wage records come from the National Directory of New Hires. *** Impact in a two-tailed test is statistically significant at the 1-percent level, ** at the 5-percent level, * at the 10- percent level.

term evidence (i.e. longer than four years) has yet to be established.²¹

Though the sum of the evidence I have discussed supports the claim that non-cognitive skills are important for labor market success, none of these research designs have isolated the effect of non-cognitive skills training alone.²² There are, however, a handful of recent randomized evaluations of non-cognitive-skills-only training programs in various developing countries. In Jordan, [Groh et al. \(2016\)](#) find that a soft-skills training program targeted to female community college graduates has no effect on employment up to two years after the program. In Togo, a small West African country, [Campos et al. \(2017\)](#) find that a “psychology-based personal initiative training” that taught entrepreneurs to have a “proactive mindset” increased their firm’s profits by 30% two years later, which was larger than the gain from a concurrently administered financial and marketing training. In the Dominican Republic, [Acevedo et al. \(2017\)](#) find that a soft-skills only arm of “Programa Juventud y Empleo”, a vocational and non-cognitive training program, had short term

²¹ A medium-term extension of [Fein and Hamadyk \(2018\)](#) is scheduled to be released in 2020 by [Abt Associates](#).

²² Year Up, however, is in the process of developing a professional skills only curriculum ([Career Labs](#)) for a shortened and easily deployable version of this aspect of the program. This could serve as an opportunity for a targeted evaluation that isolates the impact of non-cognitive skills.

(one year) positive effects on female’s salary and employment but no effect on men’s short term labor market outcomes. Finally, [Adhvaryu et al. \(2018\)](#) find that an on-the-job soft skills training program administered to Indian garment workers increased productivity of workers by 20% and increased wages by .5% over two years. Taken together, these studies suggest that employer demand for non-cognitive skills may be a global phenomenon.

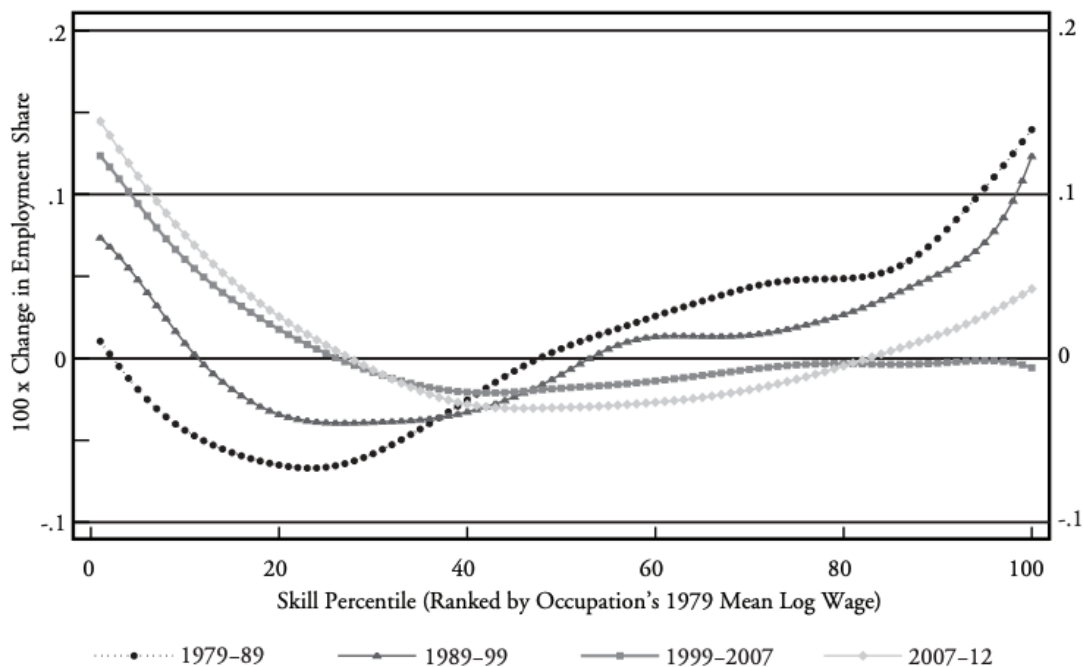
In this section, I have discussed the large body of causal evidence that non-cognitive skills are important for labor market success. Though some of these evaluations have found no evidence that non-cognitive skills impact labor market outcomes, the vast majority of papers find evidence consistent with the hypothesis that employers have and continue to value these skills in various contexts. Despite the strong support for this hypothesis, there is one major shortcoming of the literature: there has yet to be a published study (or even a working paper) evaluating the impact of non-cognitive skills only intervention in a developed country. Isolating the impact of non-cognitive skills training is crucial for policy because there is currently expert disagreement on the value in investing in non-cognitive skills alone.²³ Though there is some evidence that targeting non-cognitive skills alone has positive effects in West Africa, the Dominican Republic, and India, developed labor markets (and the US labor markets in particular) are very different, which makes it difficult to generalize these results to the US context.

4 Trends in the Labor Market Value of Non-Cognitive Skills

First documented in [Autor et al. \(2003\)](#), the introduction of computing and software into the labor market has disproportionately replaced workers in routine cognitive occupations while simultaneously increasing the productivity of workers in in non-routine problem-solving and complex occupations ([Autor et al. 2006](#); [Autor and Dorn 2013](#); [Autor 2014](#); [Deming 2017a](#); [Atalay et al. 2019](#); [Webb 2019](#)). Because many workers employed in routine cognitive jobs were middle-wage,

²³For example, [Heckman et al. \(2019\)](#), a recent review of the economics of personality literature, suggest that the “greatest growth in economic returns accrue to bundles of cognitive and non-cognitive skills, not to either separately”, citing [Caines et al. \(2017\)](#) as support. [Caines et al. \(2017\)](#) studies the increasing returns to “complex-tasks” from 1980-2005.

Figure 8: Changes in Employment Share by Occupation Wage
Autor (2014)



Notes: This is Chart 7 from [Autor \(2014\)](#). Calculated using 1980, 1990 and 2000 Census IPUMS files; American Community Survey combined file 2006–08, American Community Survey 2012. The chart plots changes in employment shares by 1980 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of an occupation’s mean log wage in the Census IPUMS 1980 5 percent extract. Employment in each occupation is calculated using workers’ hours of annual labor supply times the Census sampling weights.

their replacement by technology has caused “job-polarization” where low-wage jobs and high-wage jobs increasingly characterize the economy. To visualize this, see Figure 8, taken from [Autor \(2014\)](#) which depicts a reduction in the rate of growth in middle-wage jobs relative to high-wage and wage-income jobs. In the context of the review, it is important to note that the tasks that have been replaced by computers and software tend to require primarily cognitive skills. In fact, further evidence, documented by [Castex and Kogan Dechter \(2014\)](#) and [Beaudry et al. \(2016\)](#), suggests that there has been a collapse in employer demand for cognitive skills. If this narrative is correct, is there another type of skill that employers increasingly want instead?

Throughout the computer revolution, employer surveys inquiring about the skills they want in an employee present a potential answer: non-cognitive skills. Starting in the early 90s, multiple of these surveys were administered by both researchers and the government. Generally, these surveys

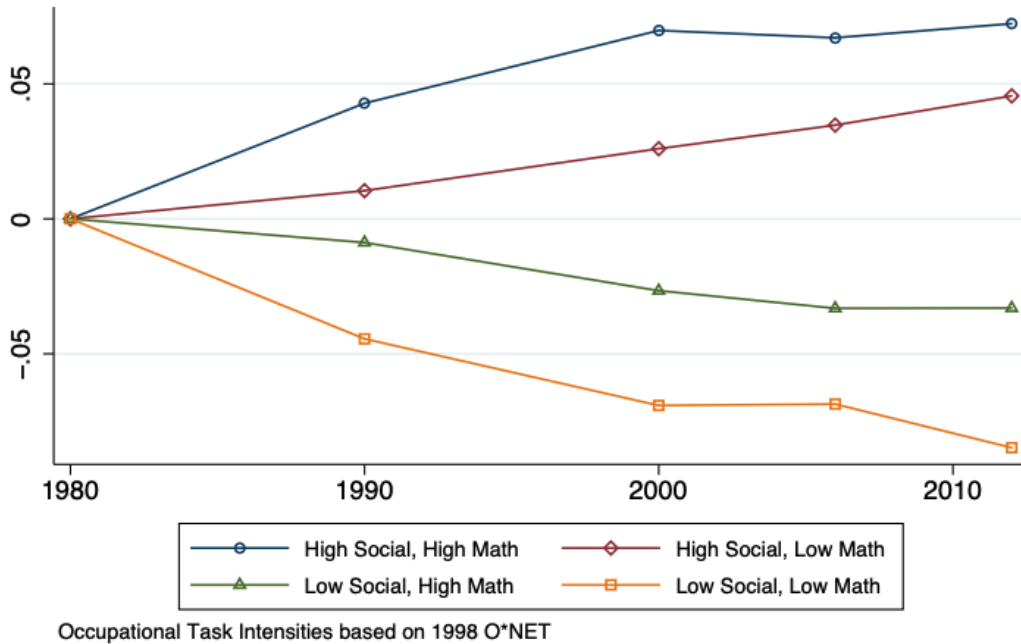
indicate that employers want workers with characteristics far beyond typical academic characteristics such as college degrees, good grades, and high test scores. For instance, respondents across the US and UK consistently list skills such as teamwork, communication, integrity, and attitude as necessary for working in their firm or commonly lacking in their current applicants ([Secretary's Commission on Achieving Necessary Skills 1991](#); [Holzer 1997](#); [Zemsky 1997](#); [Hillage et al. 2002](#); [Westwood 2004](#); [Barton 2006](#); [Washington Workforce Training Board 2008](#)).

A conceptual reason that non-cognitive skills may be relatively more valuable in an age of automation comes from [Autor \(2014\)](#). In this paper, David Autor argues that the scope for technological substitution is bounded because computer technologies primarily accomplish algorithmic processes governed by explicit rules. Humans, however, possess many capabilities that are nearly impossible to describe because we only know them tacitly. These types of skills are not codifiable, which limits the extent to which computer technology can replace human labor. This substitutability constraint is what Autor calls “Polanyi’s paradox”, following the observation by physical chemist and philosopher [Polanyi \(1966\)](#) that “We know more than we can tell.” It is important to notice that tacit skills (e.g. creativity, emotional intelligence, and social skills) tend to be non-cognitive. And, explicit skills (e.g. coding, computing, and calculating) tend to be cognitive. Thus, the theory in [Autor \(2014\)](#) simultaneously explains the reduction in firm demands for cognitive skills and predicts that firms should increase their relative demand for non-cognitive skills.

Recent research has found quantitative support for this. For example, [Deming \(2017a\)](#) studies how the importance of social skills in the labor market has changed from 1980 to 2012 in the United States. He finds that jobs requiring a high level of social interaction grew by 12 percentage points as a share of the US labor force, while jobs that are math-intensive and require a low level of social interaction shrank by 3.3 percentage points (see Figure 9). Additionally, using the NLSY, he finds that the return to social skills was significantly greater after the year 2000. Deming rationalizes these findings with a model that conceptualizes social skill as reducing the cost of teamwork by making it easier to “trade tasks” between teammates. As firms increasingly demand that workers perform non-routine, social-skill intensive tasks, this bids up the return to social skill. Deming sees

this as perfectly consistent with the decline in routine cognitive employment described in Autor et al. (2003).

Figure 9: Cumulative Changes in Employment Share by Occupation Task Intensity
Deming (2017a)



Notes: This is Figure 4 from Deming (2017a). Calculated using 1980–2000 Census and 2005–2013 American Community Survey. Each line plots 100 times the change in employment share (relative to a 1980 baseline) between 1990 and 2012 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET.

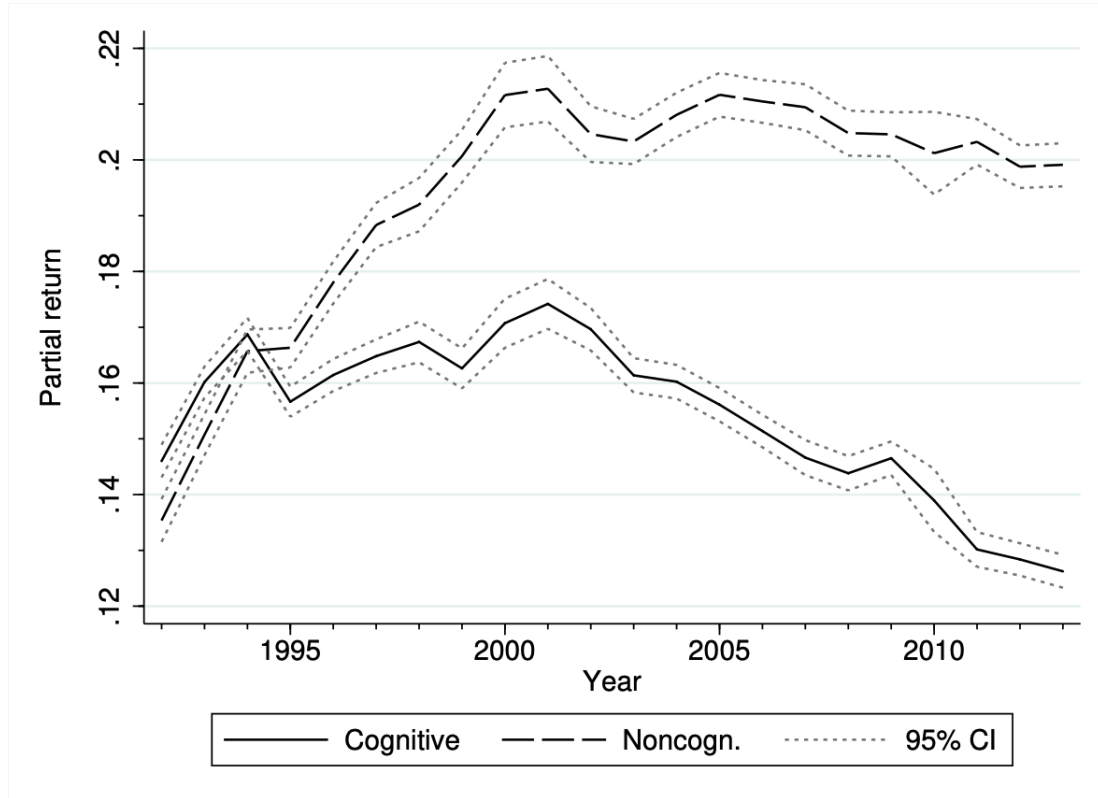
Complementing this, Deming and Noray (2018) document that, from 2007 to 2019, the proportion of online job ads²⁴ that include at least one character (aka non-cognitive) skill increased by 12.7 percentage points and the proportion of ads that include at least one social skill increased by 11.4 percentage points. In comparison, the proportion of ads that include at least one cognitive skill only increased by 8.5 percentage points. Furthermore, using regression analysis on Swedish administrative data, Edin et al. (2018) document that, from 1992–2013 for mid-career-age men, the return to non-cognitive skill in the labor market increased by 6–7 percentage points while the return to cognitive skill declined by 1–2 percentage points over the same period (see Figure

²⁴Deming and Noray (2018) use data from Burning Glass Technologies, an employment analytics and labor market information firm that scrapes job vacancy data from more than 40,000 online job boards and company websites. Burning Glass claims to scrape the near-universe of online job ads.

10).²⁵

Figure 10: Changing Earnings Return to Cognitive and Non-Cognitive Skill (Sweden)

Edin et al. (2018)



Notes: This is panel b of Figure 3 from [Edin et al. \(2018\)](#). This figure depicts the average increase in the natural log of wage from a one standard deviation increase in an index of cognitive or non-cognitive skill. Wage data was collected by Statistics Norway. Sample contains only men from age 38-42 because they are relatively insulated from cyclical labor market change.

To summarize, in the past three decades computers and software have entered and filtered through the economy, making many routine cognitive occupations unnecessary. Workers in jobs that require more flexible, complicated, and tacit knowledge have proved difficult to codify, and therefore difficult to replace. Furthermore, in the hands of workers with these non-cognitive skills, computer technologies have made them relatively more productive. Together, these forces seem to have reduced the relative demand for cognitive skills and increased the relative demand for non-cognitive skills. A key policy-relevant question, then, is whether we should expect this to continue.

²⁵There is also suggestive evidence from Finnish data that increasingly valuable non-cognitive skills such as sociability are becoming more common, which is what we should expect if people are investing in skills rationally ([Jokela et al. 2017](#)).

Though such forecasting is difficult, I think there are two pieces of evidence that suggest the answer is yes.

First, [Webb \(2019\)](#) explores which jobs are most likely to be replaced by the next wave of Artificial Intelligence by matching the text of recent AI patents to job descriptions. He finds that jobs requiring interpersonal skills are least replaceable by software and are also among the least likely to be replaced by coming AI technologies. In the second study, [Autor and Salomons \(2019\)](#) document three categories of new jobs, which are jobs that have grown enough in recent years that they now appear in the dictionary of occupational titles. One of the categories they uncover they call “wealth work”, referring to occupations that perform services primarily for relatively high-income clients. Each of the jobs in this category – such as nail technicians, dog groomers, personal trainers, and counselors – requires interpersonal skills.

5 Signaling Non-Cognitive Skills to Employers

In the early 1990’s, the US government conducted a large employer survey called the SCANS report, with the intention of figuring out what kinds of skills employers most valued ([Secretary’s Commission on Achieving Necessary Skills 1991](#); [Heckman et al. 2019](#)). Responses to this survey revealed five types of skills that employers wanted in a good employee : “[1] the ability to allocate resources (i.e. time, money, facilities, etc.), [2] interpersonal skills (such as teamwork, teaching others, and leadership), [3] the ability to acquire and to use information, [4] the ability to understand systems, and [5] the ability to work well with technology.” Furthermore, responses to other smaller surveys conducted around the same time indicated that skills such as responsibility, integrity, self-management, attitude, and communication skills, are as important as other academic skills such as schooling, grades and test scores ([Holzer 1997](#); [Zemsky 1997](#); [Heckman et al. 2019](#)).

Two things stand out about this list of skills. First, there are a lot of them. Second, employers do not always refer to the skills they want with the same terms that researchers do. And, this says nothing of what the average worker calls these skills. This raises a key question: given the

wide variety of names for these skills, do employers notice or even understand what is being signaled when a job-seeker attempts to express that they have non-cognitive skills? Is there value in signaling these skills at all?

The best evidence on this question comes from [Piopiunik et al. \(2020\)](#) and [Bassi and Nansamba \(2019\)](#). In the former, the authors perform a resumé correspondence study (often called an “audit study”) in Germany. Specifically, the authors produce a set of resumes that are identical except a randomly chosen subset that include a signal social skill, maturity, or both. The authors then send these resumes to HR managers and compare differences in the likelihood of receiving a callback by non-cognitive skill signals.²⁶ To signal social skills, the authors indicate that the fake applicant participated in social volunteering (i.e. working with youth, the elderly, and teaching German language courses) and played a team sport. To signal maturity, the authors indicate that the fake applicant is a year older, while holding their graduating class constant.

The authors find that signaling social skills via social volunteering causes between a 37 percentage point increase in the likelihood that both male and female applicants receive an invitation to interview. This is roughly equivalent to the effect of boosting GPA by two letter grades. Additionally, they find that signaling maturity is associated with a 24 percentage point increase in the likelihood of receiving an invitation to interview, but this effect is concentrated among males.²⁷

[Bassi and Nansamba \(2019\)](#) tackle a similar question in a very different setting: Uganda. In this experiment, the authors assess the non-cognitive skills of a sample of workers and randomly vary whether certificates of their performance are disclosed to the workers themselves and/or potential employers. The authors find two main results: (1) workers who receive information of their non-cognitive skills become more optimistic about their labor market prospects and (2) managers,

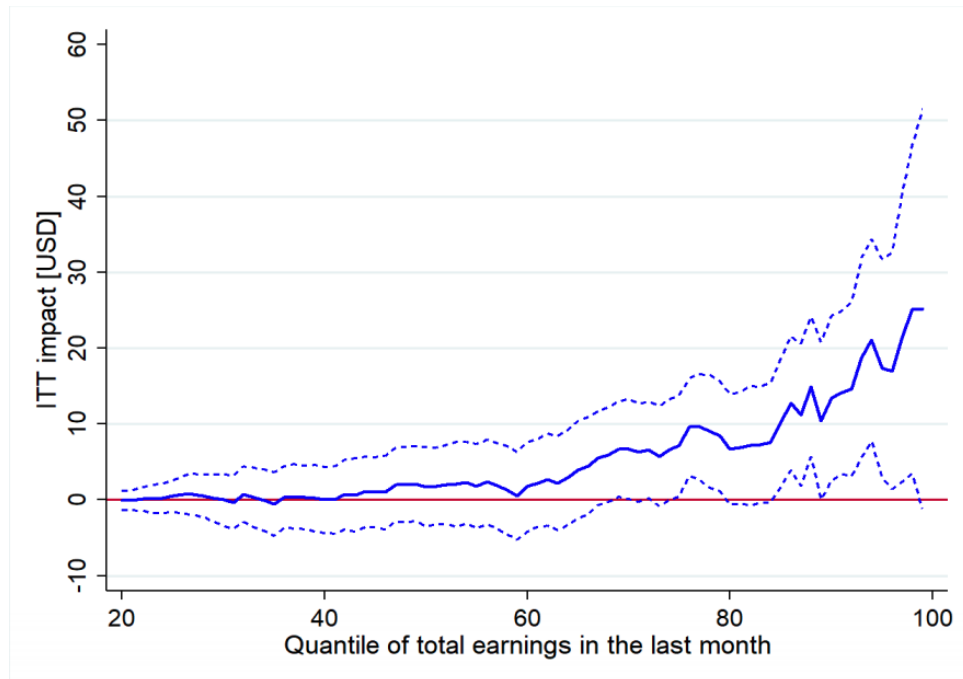
²⁶The authors also explore the value of signaling cognitive skills, which I do not discuss in detail because of the nature of this review. Generally, the authors find the classic result that evidence of these skills increases the likelihood of being invited for an interview.

²⁷A related study is [Kaas and Manger \(2012\)](#), which studies Turkish discrimination in Germany using a correspondence study. Rather than just randomizing signals of race (in this case, Turkish-sounding vs. German names) on job applications, they also randomize whether applicants receive reference letters that comment on the applicant’s “conscientiousness” and “openness” (two of the Big Five Personality Traits commonly used by personality psychologists). They find that including the reference letters eliminates anti-Turkish discrimination in their sample. This suggests that signaling non-cognitive skills may be particularly helpful for minority groups, though further research is required to generalize from this study.

particularly at high-productivity firms, are more likely to improve their assessment of and hire workers with visible non-cognitive skill certificates if they get at least a passing grade on the assessment. Ultimately, this leads the better workers to match with the better firms (i.e. assortative matching). To visualize this, see Figure 11, which plots the effects of the intervention on earnings by percentile, showing that effects are concentrated among high earners. The authors conclude by arguing that the inability to signal this ability up front likely creates market inefficiencies. Though this study was conducted in a relatively unique environment, it has the advantage of measuring impacts on real job applicants and tracking actual hires.

Figure 11: Impact of Signaling Non-Cognitive Skills by Earnings

Bassi and Nansamba (2019)



Notes: This is Figure 5 from [Bassi and Nansamba \(2019\)](#). The figure reports quantile regression estimates of treatment effects on total labor earnings from all activities in the month prior to the survey, with 90% confidence intervals. The regressions control for stratification variables (dummies for region and sector), a dummy for second follow up and dummies for month of interview. In addition, all regressions control for the following worker characteristics measured at baseline: a dummy for whether the worker had a pass grade (C or above) on all five soft skills measured in the baseline assessments and disclosed on the Treatment group certificates; age and age squared; dummy for female; years of formal education; duration (in years) of the vocational training program the worker was attending at baseline; dummy for any past work experience; expected earnings at baseline.

Altogether, this research suggests that signaling non-cognitive skills to potential employers matters, but more research on this question is needed. At least three key questions remain unanswered: (1) “Is there value in signaling non-cognitive skills in the US?”, (2) “What is the most

effective way job-seekers can describe their non-cognitive skills if they want employers to understand what they mean?”, and (3) “What are the minimal set of non-cognitive skills that matter?” Though these questions are currently difficult to answer, the rise of big data and the decreasing cost of measuring skills may provide an avenue for tackling them. For example, large job-matching platforms like Monster, Indeed, and ZipRecruiter could, at low cost, give random nudges to job-seekers to include non-cognitive skills on their resumes, and measure whether these job-seekers are more likely to be contacted by employers. Additionally, skill-measurement companies like Knack and Pymetrics, both of which use micro-data from digital games to measure cognitive and non-cognitive capabilities, could measure how various skills and traits are correlated among various segments of the population, which would demonstrate which skills are redundant. Thus, I remain hopeful that these questions can and will be answered.

6 Conclusion

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