Volume Title: Education, Skills, and Technical Change: Implications for Future US GDP Growth

Volume Authors/Editors: Charles R. Hulten and Valerie A. Ramey, editors

Volume Publisher: University of Chicago Press

Volume ISBNs: 978-0-226-56780-8 (cloth); 978-0-226-56794-5 (electronic); 0-226-56780-X (cloth)

Volume URL: http://www.nber.org/books/hult-12

Conference Date: October 16-17, 2015

Publication Date: December 2018

Chapter Title: Noncognitive Skills as Human Capital

Chapter Author(s): Shelly Lundberg

Chapter URL: http://www.nber.org/chapters/c13701

Chapter pages in book: (p. 219 – 243)

6

Noncognitive Skills as Human Capital

Shelly Lundberg

6.1 Introduction

Human capital plays a central role in all analyses of economic growth. In empirical growth models, the standard proxy for human capital is educational attainment, but this is an indirect and very imperfect measure of labor skills. Educational attainment is also a skill measure that is not comparable across nations (or over time) due to variation in educational quality. Hanushek and Kimko (2000) found that scores on international examinations are more important than years of educational attainment for economic growth, and a robust literature concerning the role of cognitive skills in economic development has emerged (Hanushek and Woessmann 2008). As evidence grows that other, so-called noncognitive, skills have large and significant impacts on individual earnings and other economic outcomes, the research on growth may need to incorporate these additional dimensions of human capital. We are far, however, from a clear understanding of how to define and measure noncognitive skills in a way that would allow for meaningful cross-country analysis.

The idea that noncognitive skills are both important outcomes of the educational process and inputs to human capital production has a long history in labor economics. Bowles and Gintis (1976), in their classic study of

Shelly Lundberg is the Leonard Broom Professor of Demography at the University of California, Santa Barbara, adjunct professor at the University of Bergen, and a research fellow of the IZA.

I appreciate helpful comments from David Deming, Charles Hulten, Valerie Ramey, and Jenna Stearns, and the excellent assistance I have received from Sarah Bana. For acknowledgments, sources of research support, and disclosure of the author's material financial relationships, if any, please see http://www.nber.org/chapters/c13701.ack.

the American education system, assert that "employer-valued attributes," including perseverance and punctuality, are important products of schooling. Weiss (1988) shows that nearly all of the relationship between high school graduation and earnings can be explained by the lower quit propensities and lower rates of absenteeism of high school graduates compared to high school dropouts. Heckman and a number of collaborators have worked to incorporate noncognitive skills into the economic analysis of individual achievement, noting that "personality, persistence, motivation, and charm matter for success in life" (Heckman, Stixrud, and Urzua 2006). There is now considerable evidence that these traits, in addition to cognitive ability and academic achievement, are important determinants of economic success. In particular, socioeconomic gaps in noncognitive traits at early ages are implicated in the intergenerational transmission of inequality. This represents an important shift in economists' conception of human capital, moving beyond brains and brawn to incorporate a broad set of psychosocial capabilities.

In a very short period of time, a substantial literature has appeared on noncognitive skills—their economic payoffs, the sources of socioeconomic disparities in skill levels, and the possible role of early investments in augmenting noncognitive skills and reducing these disparities. A recent Organisation for Economic Co-operation and Development (OECD) report by Kautz et al. (2015, 7) reviews much of this literature, with a particular focus on the outcomes of early interventions, and reaches the following conclusions: (a) noncognitive skills are valuable in school and in the labor market, (b) reliable measures of noncognitive skills are available, and (c) individual skills are stable at a point in time, but can be shaped in the early years of life.

The first of these conclusions is undoubtedly true, and the evidence for the third is accumulating rapidly. The second conclusion is perhaps premature—some serious issues persist with respect to the measurement of noncognitive skills, and especially the estimation of skill disparities between groups. One issue is a lack of consensus about what noncognitive skills are, and the absence of a consistent set of metrics that can be applied across studies. In Kautz et al., noncognitive skills are defined as "personality traits, goals, character, motivations, and preferences that are valued in the labour market, in school, and in many other domains," which is an astonishingly broad characterization. A second issue is the widespread use of behavior as, de facto, a pure indicator of skill, rather than an outcome that also depends on incentives, beliefs, and situation. The comparability of such measures across population groups defined by gender, ethnicity, or socioeconomic status or across nations is highly suspect.

The label "noncognitive" is a controversial one and psychologists disapprove, informally, of its popularity among economists. Alternative terms have been used, including socioemotional skills, soft skills, personality skills and, most recently, character, but I will use "noncognitive" consistently because it is familiar and a clearly superior alternative has not emerged. Indices of children's noncognitive skills are usually based on teacher and parent reports of the child's behavior, including their ability to focus attention on tasks, social skills, and externalizing (disruptive or aggressive) behavior. Measures of adult skills are sometimes based on behavioral assessments (or administrative records such as criminal histories) but more commonly rely on self-reports of the individual's behavioral tendencies, feelings, or beliefs, including assessments of self-esteem, conscientiousness, and persistence.

In this chapter, I review some of the recent literature on the association between noncognitive skill metrics and important economic outcomes such as educational attainment and earnings. Some characteristic patterns of effects are illustrated using two longitudinal surveys that track recent cohorts from adolescence to young adulthood, but have not been extensively used in previous studies of noncognitive skills. I find that some measures of social and emotional problems in early adolescence have strong negative associations with educational attainment, while others do not. All skill proxies have weak effects on earnings conditional on education. Parental and youth reports of the same behaviors have independent influences on education outcomes. Though this is a standard empirical exercise in this literature, the results are not easy to interpret. They do suggest that adolescent noncognitive skills may be particularly important in navigating the path through school, rather than having independent influences on labor productivity. I also show, using an example involving impulsivity and crime, that measurement and endogeneity problems make one common empirical exercise—the documentation of skill gaps between groups and assessments of the contribution of these gaps to inequality—extremely problematic.

The research agenda on incorporating noncognitive skills into economic growth models is rather daunting. First, we need some agreement on a standard battery of noncognitive skill assessments at different stages of human development. The early childhood intervention literature has been able to rely on measures used by developmental psychologists, but as we move through childhood to adolescence and adulthood, the situation becomes rather chaotic since there are too many behavioral domains and psychological inventories to choose from. Second, we need research that disentangles the effect of skills on economic outcomes from impacts that occur through other channels, parental and environmental, that have helped to shape these skills. This standard identification problem has been inadequately addressed in the current literature. Finally, evidence is emerging that the returns to traits that have been labeled noncognitive skills are highly heterogeneous—traits that are useful in some social, economic, and cultural environments may be harmful in others. This complicates international comparisons in a way that does not arise with cognitive skills.

Despite these difficulties, broadening the economic concept of human capital is an important exercise. Research in neurobiology and developmental psychology indicates that noncognitive skills emerge from the same developmental processes as conventionally measured cognitive abilities. Early interventions that enrich children's environments and reduce stress can lead to improvements in executive functioning that foster the ability to regulate emotions and attention, as well as to acquire vocabulary. These skills are strongly predictive of educational outcomes and attainment, and may be leveraged by complementarities between sets of skills in the human capital acquisition process. Early investments in noncognitive skills may have important positive effects on growth by increasing the returns to other educational inputs. Finally, as technological change transforms the labor market and the task requirements of jobs, the returns to skills that foster effective human interaction seem likely to continue to rise (Deming 2017).

6.2 Noncognitive Skills Enter the Human Capital Literature

New studies that document the returns to psychosocial traits and behavioral tendencies, or the impact of early treatments on these traits, emerge almost daily. Researchers have found that a variety of such indicators are significant predictors of economic outcomes including wages, earnings, health, crime, and relationship stability. One of the key features of this literature is the bewildering array of personal traits and actions that the "noncognitive skill" label has been applied to, including teacher assessments of social skills, parental reports of toddler temperament, self-reported beliefs about personal control, and administrative records of school suspensions. In general, these are measures of convenience, adopted by researchers because they happen to be available on surveys or administrative registers and turn out to be correlated with interesting outcomes. These noncognitive metrics can be sorted into three broad categories:

1. Self-assessments. These instruments ask individuals to respond to questions that indicate "This is what I am like" or "This is what I believe." Personality traits are perhaps the most commonly used self-assessments in the economics literature. For example, a positive response to "I sympathize with others' feelings" is one component of the Big Five personality trait, agreeableness, while agreeing with "When I make plans, I am almost certain that I can make them work" is indicative of an internal locus of control (or high self-efficacy).

2. Parent/teacher reports of a child's behavior, tendencies, or abilities. Behavior problem indices that include measures of externalizing and internalizing behavior, as well as reports of persistence, ability to focus, and social skills, have been extensively used by psychologists and education researchers, and are available in many large-scale data sets.

3. Administrative records. Registers of school disciplinary actions, crimi-

nal justice contacts, or military service can sometimes be linked to subsequent economic outcomes.

The more recent economics literature on noncognitive skills (including the controversial label) came into prominence with two studies by James Heckman and coauthors. One of these relied on behavioral indicators of skills, while the other used self-assessments. Heckman and Rubinstein (2001) find that General Education Development/Diploma (GED) recipients are more likely to engage in drug use and to commit minor crimes than conventional high school graduates. They infer that the absence of a positive economic return to GED recipiency is due to a shortfall in noncognitive skills among those who receive this credential. Heckman, Stixrud, and Urzua (2006), using adolescent measures of self-efficacy and self-esteem in the National Longitudinal Survey of Youth 1979 as indicators of noncognitive ability, find that noncognitive and cognitive skills are equally important in determining a variety of economic and social outcomes. Both of these papers have been influential and have alerted economists to the potential significance of traits other than cognitive ability that contribute to economic success.

6.2.1 Personality, Self-Control, and Social Skills

In the first decade of the century, many researchers took advantage of newly available (self-assessed) personality inventories included in large longitudinal surveys, including the British Household Panel Study (BHPS), the German Socio-Economic Panel Study (SOEP), and the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Most surveys included a fifteen-item short form of the "Big Five" personality inventory, which consists of the traits openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism/emotional stability. The Big Five was developed and extensively evaluated by psychologists, and is broadly accepted as a meaningful and consistent construct for describing human differences (Goldberg 1981).

Economic studies of personality focused initially on the determinants of earnings and other labor market outcomes. In general, high emotional stability and low agreeableness have been found to be positively associated with earnings for men, and in some cases for women (Mueller and Plug 2006; Heineck 2011; Nyhus and Pons 2005). Personality traits also influence the sorting of workers across occupations, and this can be interpreted as the result of either varying preferences over job attributes or occupation-specific determinants of productivity (Filer 1986; Krueger and Schkade 2008). Nandi and Nicoletti (2014) decompose the pay gaps between personality groups in the BHPS data into components that can be explained by personality-based differences in occupation, education, work experience, and unexplained components. They find that the observed pay premium for openness can be explained by higher education and by sorting into higher-paid occupations, but that the pay premium for extraversion and the penalties for neuroticism and agreeableness cannot. Another personality construct, self-efficacy or locus of control, has also been found to be positively related to a variety of labor market outcomes (Heineck and Anger 2010; Cobb-Clark, Caliendo, and Uhlendorff 2015; Cobb-Clark 2015). Personality and other socioemotional traits also have important associations with the propensity to marry and with relationship stability (Lundberg 2012, 2015).

Even though the study of personality originated as an attempt to understand why some highly intelligent individuals perform well in school and in later life while others do not, the relationship between personality and education has not received as much attention from economists as have personality effects on earnings. Pioneers in the development of intelligence quotient (IQ) tests, such as Binet and Terman, were aware of the significance of qualities other than cognitive ability in determining success, and identified the key features of this dimension of "character" as perseverance and attentiveness—aspects of the Big Five trait, conscientiousness (Almlund et al. 2011). A large literature in psychology and education finds that conscientiousness and behaviors related to conscientiousness, such as persistence and self-control, are strongly predictive of grades in school and other measures of educational success.

Measuring noncognitive skills via self-assessments such as personality inventories cannot begin before middle childhood at the earliest. Assessments of younger children rely on behavioral measures, and the "marshmallow studies" have produced the best known of these. Beginning in the late 1960s, psychologist Walter Mischel led a series of studies that showed a strong association between the ability to delay gratification as a four-year-old and later test scores, educational attainment, and health (Mischel, Ebbesen, and Raskoff Zeiss 1972). Larger studies have used observational measures such as parent and teacher reports of externalizing behavior—arguing, fighting, acting impulsively or disruptively—and social skills. Children from disadvantaged backgrounds begin school well behind their peers in the ability to focus their attention and control their impulses, and these gaps tend to persist as they progress through school. The predictive power of early assessments vary: teacher evaluations of eighth grade misbehavior are correlated with educational and labor market outcomes (Segal 2013), but some studies fail to find any relationship between school-entry skills such as attention and later outcomes (Duncan and Magnuson 2011).

Recent years have seen many creative uses of administrative and survey data to infer noncognitive skills and link them to later outcomes. For example, a psychologist's assessment of the suitability of a young man for military service predicts his suitability for other jobs as well (Lindqvist and Vestman 2011), and interviewer reports of survey respondent fidgeting are correlated with later economic outcomes (Cadena and Keys 2015).

6.2.2 What Are Noncognitive Skills and Where Do They Come From?

Critics have objected to the use of the label "noncognitive" skills to describe any productive characteristic that is not measured in standard cognitive batteries and academic achievement tests. This is because behaviors such as task persistence and effective social interaction require cognitive input in a way that is not clearly distinct from the cognitive demands of completing a Raven's Matrices test. The unifying principle in this view of human skills is the psychological concept of executive functioning, an umbrella term for the management of cognitive processes. A recent World Bank report on early development links cognitive and noncognitive skills through the developmental process:

> The cognitive components of self-regulation, referred to as executive function, include the ability to direct attention, shift perspective, and adapt flexibly to changes (cognitive flexibility); retain information (working memory); and inhibit automatic or impulsive responses in order to achieve a goal such as problem solving (impulse control). . . . Self-regulation also includes emotional components such as regulating one's emotions, exhibiting self-control, and delaying gratification to enjoy a future reward. (World Bank 2015, 100)

Behavioral inhibition or self-regulation is at the core of most identified noncognitive, as well as cognitive, capabilities. The ability to focus on schoolwork, get along with classmates, abstain from drugs, and persevere on tasks is a set of skills with the same developmental origins as the ability to read well and solve math problems. The role of executive function in regulating behavior will vary depending on circumstances and developmental stages, but the consistent importance of cognitive control in shaping a broad range of capabilities highlights the inaptness of the term "noncognitive."

The case for treating noncognitive skills as a type of human capital is that many dimensions, such as self-control, appear to be relatively stable, but augmentable, traits that enhance task performance, increase labor productivity, and contribute to positive economic outcomes. The question "where do they come from?" is only beginning to be answered. Personality traits are strongly heritable, and twin studies find that 40–60 percent of variation in personality is genetic (Bouchard and Loehlin 2001; Anger 2012). Advances in neuroscience, molecular biology, developmental psychology, and economics are beginning to link deficits in a broad range of behavioral, health, and cognitive abilities to early experiences and environmental conditions, including toxic stress and pollution (Shonkoff et al. 2012; Currie 2011). The implication is that the mental regulatory skills represented by the term executive functioning are affected by early (including prenatal) conditions.

Kautz et al. (2015) provide a very comprehensive survey of interventions designed to improve cognitive and noncognitive skills at a variety of ages, from infancy through adolescence. For most programs, the evidence for a treatment effect on noncognitive skills is inferential: the intervention has no measurable lasting impact on cognitive or academic abilities, but does have a long-term positive effect on education, employment, or crime. The best-known set of results is perhaps the impact of the Perry Preschool Project, an intensive program for three- to four-year-old low-income children with treatment and control groups that had long-term impacts on test scores, adult crime, and male income, though no lasting effect on IQ. A recent paper bolsters the argument that these effects were due to a noncognitive skill increase by showing that there were intermediate effects on indices of externalizing behavior and (female) academic motivation (Heckman, Pinto, and Savelyev 2013).[1] The Jamaican Supplementation Study provided two years of nutritional supplements and a parenting intervention that encouraged stimulation of stunted children age nine to twenty-four months at the beginning of the program. The stimulation treatment outperformed the nutritional treatment, with substantial effects on adult earnings and on cognitive and psychosocial skills in late adolescence (Gertler et al. 2014). There are few examples of interventions at later ages with long-term follow-up, but Project Star, in which some children were randomly assigned to smaller kindergarten classes, had no lasting effect on test scores but appeared to lead to higher earnings in early adulthood (Chetty et al. 2011). Following the success of the Jamaican study, many recent interventions have focused on improving parenting as a way to reach children very early in life. These include programs that encourage parents to interact with children in developmentally appropriate ways and others that directly target maternal stress and mental health issues that may impact parenting quality.[2]

Treating noncognitive skills as a form of human capital raises one rather confusing issue: Is it more appropriate to think of the varied indicators that have appeared in the recent economics literature as skills, or as preferences? Referring to psychological traits as "skills" is an attempt to maintain the economic distinction between preferences and constraints, but in fact, the line is rather blurred. For example, the personality trait "extraversion" reflects both social skills and an orientation toward social interaction. In their analysis of intergenerational mobility, Bowles, Gintis, and Osborne (2001) emphasize the role of parents and schools in passing on "incentive-enhancing preferences" (such as patience and self-control) as an important mechanism for transmitting economic privilege across generations. Intuitively, the self-regulation that leads to deferred gratification in the marshmallow test must be closely allied with our concept of time preference. Yet,

1. Two older programs (Perry Preschool and Abecedarian) are positive outliers among the large set of early childhood education programs in their impacts on later human capital, and we know little about the connections between program components and particular sets of skills (Duncan and Magnuson 2013).

2. See the review in World Bank (2015, chapter 5).

the empirical associations between personality and economic preference parameters are very weak (Almlund et al. 2011; Rustichini et al. 2012) and one study finds that personality and preference indicators have largely independent effects on a large set of outcomes, including health, life satisfaction, wage, unemployment, and education (Becker et al. 2012). For noncognitive skills, we have no conceptual framework comparable to the choice theory that defines preference parameters, and this impedes any effort to move beyond a piecemeal approach to noncognitive skills and develop a standardized set of instruments.

6.3 Noncognitive Skills and Adult Outcomes in NLSY97 and Add Health

To illustrate some of the characteristics of early noncognitive skill measures as predictors of future educational attainment, wages, and employment, I use data from the National Longitudinal Survey of Youth 1997 (NLSY97) and the National Longitudinal Study of Adolescent to Adult Health (Add Health), which follow similar recent cohorts from early adolescence to young adulthood. The first wave of each study includes a set of noncognitive skill indicators, ranging from skimpy in NLSY97 to abundant in Add Health, that has been relatively unutilized by economists. The purpose of this exercise is to choose, a priori, a promising and typical set of indicators of adolescent angst, confidence, and behavioral difficulties, to see whether they predict later educational attainment and labor market outcomes, and to report all the results transparently and comprehensively. I find that some plausible adolescent noncognitive skill indicators are significant predictors of educational attainment while others, equally promising, are not, and that all are weak predictors of earnings and wages. For simplicity, I report only the results for the male subsamples, though the patterns in the female models are very similar.

6.3.1 National Longitudinal Survey of Youth 1997 (NLSY97)

The NLSY97 began with a nationally representative sample of 9,000 youths who were twelve to sixteen years old at the first wave and twenty-six to thirty-two when they were interviewed in 2011–2012. In Round 1, a version of the Armed Services Vocational Aptitude Battery (ASVAB) was administered, so we have a measure of academic skills and knowledge of the sort that is widely used as a measure of “cognitive skills,” and also several indicators of noncognitive skills. This is in no sense a remarkable set of skill measures, but it does include a set of noncognitive indicators that are asked of both parents and children, which is relatively rare in large surveys. Also, the survey subjects are old enough in the last round that completed education and usable labor market information is available for almost all of them.

To measure behavioral and emotional problems in the first wave of the

NLSY97, a set of six items that were developed as indicators of children's mental health for the National Health Interview Survey (NHIS) were used. These items were, in turn, used as part of the Child Behavior Checklist (Achenbach and Edelbrock 1981). The items selected for the NHIS were those that provided the best discrimination between children who were referred or not referred for mental health services, by age category and gender. The NLSY97 uses items selected for boys and girls age twelve to seventeen, and each is asked of the parent as well as the youth. The four items that are asked of boys are whether he (a) has trouble concentrating or paying attention, (b) doesn't get along with other kids, (c) lies and cheats, and (d) is unhappy, sad, or depressed. These Achenbach index items are coded here as binary with "sometimes/somewhat true" combined with "often true" (a rare response). Factor analysis indicates that these measures cannot be combined into a mental health index, and so they are entered into the education and labor market outcome models separately. There is a general tendency for these reports of problem behaviors to fall with mother's education, though there are exceptions (e.g., mother reports that sons are depressed). The mean ASVAB percentile is strongly increasing in mother's education, as is an optimism index (constructed from four items such as "In uncertain times, I usually expect the best"). Youths report substantially higher rates of problem behaviors than do parents, on average, and the correlation between parent and youth responses is relatively low for most items (.19 to .30).

Table 6.1 reports the results for ordered probit models of educational attainment (defined in six levels from less than high school through postgraduate degree) and linear probability models of college graduation for men, where the independent variables include youth and parent-reported behavior problems, optimism, cognitive ability, and maternal characteristics. One self-reported noncognitive measure is significantly associated with educational attainment (trouble paying attention) as are two parent-reported items (lies or cheats and depressed). If both parent and youth reports are included in the model, the significance levels and magnitude of these coefficients change very little. These associations are substantial—a self-report of "trouble paying attention" by a teenager is equivalent to a decrease of 10 ASVAB percentiles in the categorical education model. The optimism index is never significantly associated with education (or with other outcomes).

Table 6.2 shows that, for this particular set of noncognitive indicators, there is little direct influence on wages and employment[3] once educational attainment is controlled for. Personality studies usually find significant

3. Employment is defined as positive earnings and twenty-five or more hours of work per week.

Table 6.1 **Educational attainment, men (National Longitudinal Survey of Youth 1997)**

	Educational attainment (0–5)		Bachelor's degree or above	
	(1)	(2)	(3)	(4)
Achenbach Child Behavior Checklist—Self-report				
Trouble paying attention	**−0.2360*** **		**−0.0985*** **	
	(0.0695)		(0.0228)	
Does not get along well with others	−0.0327		0.0033	
	(0.0681)		(0.0224)	
Lies or cheats	−0.0396		−0.0256	
	(0.0666)		(0.0219)	
Unhappy, sad, or depressed	0.0170		0.00218	
	(0.0681)		(0.0224)	
Achenbach Child Behavior Checklist—Parent report				
Trouble paying attention		−0.0530		−0.0221
		(0.0709)		(0.0234)
Does not get along well with others		−0.0173		−0.0079
		(0.0798)		(0.0263)
Lies or cheats		**−0.1550***		−0.0305
		(0.0711)		(0.0233)
Unhappy, sad, or depressed		**−0.2540****		**−0.0744****
		(0.0776)		(0.0255)
Optimism index	0.0188	0.0228	0.0062	0.0085
	(0.0197)	(0.0194)	(0.00649)	(0.00640)
ASVAB age-normed percentile	**0.0164*** **	**0.0161*** **	**0.0045*** **	**0.0045*** **
	(0.00140)	(0.00144)	(0.000441)	(0.000459)
Observations	1,178	1,178	1,178	1,178
Adjusted R^2			0.283	0.280

Notes: Ordered probit and linear probability models. Standard errors in parentheses. Model also includes controls for mother's education, race, ethnicity, and region.

***Significant at the 0.1 percent level.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

direct impacts of personality traits on earnings, conditional on education, but it is not uncommon for noncognitive indicators based on early reports of emotional and behavioral problems to primarily affect the education process and have little direct association with later outcomes.[4] In results not reported here, there are significant interactions between cognitive skills and

4. In fact, Papageorge, Ronda, and Zheng (2017) find that childhood externalizing behavior, though it reduces educational attainment, has a positive association with adult earnings.

Table 6.2 **Employment and wages, men (National Longitudinal Survey of Youth 1997)**

	Employment[a] (1)	Log wage (2)
GED	−0.0154	0.0942
	(0.0593)	(0.148)
HS diploma	**0.133****	**0.369****
	(0.0509)	(0.124)
Associate's degree	0.0964	**0.496****
	(0.0678)	(0.153)
Bachelor's degree	**0.243*****	**0.505*****
	(0.0631)	(0.145)
Graduate degree	**0.164***	**0.690*****
	(0.0829)	(0.183)
Achenbach Child Behavior Checklist—Parent report		
Trouble paying attention	−0.0170	−0.0164
	(0.0299)	(0.0645)
Does not get along well with others	**−0.0720***	−0.102
	(0.0332)	(0.0749)
Lies or cheats	−0.0227	0.0302
	(0.0298)	(0.0645)
Unhappy, sad, or depressed	−0.0073	−0.1300
	(0.0323)	(0.0704)
Optimism index	−0.0094	0.0136
	(0.0082)	(0.0183)
ASVAB age-normed percentile	−0.0002	0.0010
	(0.0006)	(0.0013)
Observations	1,006	772
Adjusted R^2	0.053	0.107

Notes: Standard errors in parentheses. Model also includes controls for mother's education, race, ethnicity, and region.

[a] Positive earnings and twenty-five hours or more of work a week.

***Significant at the 0.1 percent level.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

some of the noncognitive measures—the effect of the ASVAB percentile on college graduation is substantially attenuated for men whose parents reported that they "did not get along well with others" when young. One possible interpretation of this result is that social skills and self-control alter the human capital production function by enhancing the learning environment, but the potential endogeneity of these measures is worth pointing out: parental reports that their child has poor social skills may be a signal of parental characteristics that affect school success rather than a valid measure of the child's noncognitive skills (Datta Gupta, Lausten, and Pozzoli 2012).

6.3.2 National Longitudinal Study of Adolescent to Adult Health (Add Health)[5]

The Add Health study is a good companion to the NLSY97, since it surveys almost the same birth cohorts and follows them for a similar period, but provides a very different set of noncognitive skill indicators in Wave I. The study began in 1994–1995 with a nationally representative, school-based survey of more than 90,000 students in grades 7 through 12. About 20,000 respondents were followed in subsequent surveys, the last of which (Wave IV) was conducted in 2007–2008 when the respondents were between twenty-four and thirty-two years of age. To increase comparability with the NLSY97 results, I restrict the sample to men. By Wave IV most, though not all, of these young men will have completed their formal education and acquired some work experience.

The Add Health data is very rich, and Wave I contains a wealth of questions about the adolescents' attitudes, beliefs, and behaviors that could be used to construct noncognitive skill measures. I have chosen to include fairly standard indices of self-esteem and depression, and constructed a school problems index from youth reports of problems experienced with classmates, teachers, or homework. Finally, I have included a positive response to the question "When making decisions, you usually go with your 'gut feeling' without thinking too much about the consequences of each alternative" as a measure of impulsivity. Cognitive skills are measured with a computer-assisted version of the Peabody Picture Vocabulary Test administered in Wave I.

Table 6.3 shows that depression and self-esteem have small and generally insignificant associations with educational attainment (or the probability of graduating from college), but the school problems index and impulsivity have large and significant associations, ranging from one-third to one-half of the magnitude of cognitive ability (all measures are standardized). As with the NLSY97 measures, there are no significant effects of noncognitive skills measured in early and mid-adolescence on labor market outcomes (in this case log earnings) once educational attainment has been controlled for. These results highlight the context-specificity of many measures of noncognitive skills—the emotional states and behavior problems of adolescents clearly flag educational difficulties, but are less predictive of longer-term capabilities.

5. Add Health is a program project directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill, and funded by grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from twenty-three other federal agencies and foundations. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Information on how to obtain the Add Health data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from grant P01-HD31921 for this analysis.

Table 6.3 Educational attainment and earnings, men (National Longitudinal Study of Adolescent to Adult Health)

	Educational attainment (1)	Bachelor's degree or above (2)	Log earnings (3)
HS diploma			**0.2692****
			(0.0928)
Some college			**0.3839*****
			(0.1049)
Associate's degree			**0.5020*****
			(0.1088)
Bachelor's degree			**0.6190*****
			(0.1016)
Graduate degree			**0.6392*****
			(0.1209)
School problems index	**−0.2072*****	**−0.0497*****	0.0024
	(0.0214)	(0.0070)	(0.0238)
Depression index	0.0175	0.0006	−0.0230
	(0.0219)	(0.0075)	(0.0262)
Self-esteem index	0.0331	**0.0175***	0.0062
	(0.0214)	(0.0076)	(0.0238)
Impulsivity	**−0.1169*****	**−0.0377*****	−0.0168
	(0.0200)	(0.0073)	(0.0212)
Cognitive ability (AH Picture Vocabulary Test)	**0.3561*****	**0.0920*****	**0.0867****
	(0.0230)	(0.0082)	(0.0329)
Observations	5,743	5,743	5,373
Adjusted R^2		0.203	0.094

Notes: Standard errors in parentheses. Model also includes controls for mother's education, race, and ethnicity.
***Significant at the 0.1 percent level.
**Significant at the 1 percent level.
*Significant at the 5 percent level.

In many ways, this is a typical set of nonexperimental, noncognitive skill results—we can show that some characteristics and behavioral tendencies measured relatively early in life have significant associations with later outcomes, particularly educational attainment. The interpretation of the results is difficult—clearly no causal statements would be appropriate. Problems in school can reflect deficiencies in parenting or an adverse school environment as well as adolescent skills, and it is unlikely that we could control for school and parent characteristics well enough to eliminate omitted characteristics. It is not surprising, perhaps, that reported behavior now may be strongly predictive of behavior in the future, but that association may reflect continuity in either characteristics or in circumstances.

6.4 Measurement

To date, the economics literature on noncognitive skills has made major contributions to our understanding of the production and the productivity of human capital. It has broadened our understanding of human capabilities and the multidimensional nature of productive skills, and has focused attention on the early stages of life, when executive functioning and the regulatory capacities that flow from it can be degraded or enhanced. Considerable progress has been made in modeling the production of multidimensional forms of human capital (Cunha and Heckman 2008). The development of a coherent body of empirical knowledge, however, has been hampered by the absence of a broadly accepted conceptual framework that maps developmental stages into identifiable skills and by the pursuit of an opportunistic approach to measurement. Summarizing the literature is difficult given the astonishing variety of skill proxies that economists, tapping existing data, have used. There are also conceptual problems that arise when we interpret the coefficients in tables 6.1–6.3 as estimates of the returns to noncognitive skills.

The first issue an obvious one: skills, including noncognitive ones, are endogenous. They are likely to be correlated with parental resources, environmental influences, and other skills that we don't happen to have measured, and so any causal interpretation of their apparent effects is inappropriate. The skepticism that we as a profession bring to interpreting a coefficient on a measure of IQ in an education or earnings equation seems to desert us occasionally when we are faced with a novel measure of noncognitive skill. The link between the self-control exercised by the patient children in the marshmallow experiment and their later successes may reflect not the actual return to developing patience early in life, but rather the quality of their parenting by other pathways. An interesting concrete example of this conflation can be found in Dohmen et al. (2010), who find substantial bias in the estimated "effects" of cognitive ability, risk aversion, and patience on key adult outcomes when all three measures are not included in the model.

Second, observed or reported behavior, while it may be reflective of noncognitive skills, also depends on other traits, incentives, beliefs, and situational factors, which we are unlikely to be able to control for. In the framework of Kautz et al. (2015), skills are measured based on task performance, which in turn depends on multiple skills and effort. They argue in favor of using behaviors as measures of skill, and attempting to control for other factors that influence performance, in order to avoid the reference bias that is likely to influence self-reported psychological scales.[6]

6. They show that average levels of conscientiousness across countries are not positively related to work hours, though there is a strong within-country correlation.

We now know that this identification problem affects standard measures of cognitive ability, since they depend on test performance. IQ test scores, far from being pure indicators of intellectual ability, are influenced by personality and motivation. Borghans, Meijers, and ter Weel (2008) find that substantial portions of variance in achievement test scores depend on personality, not cognitive ability, and Segal (2012) shows that incentives increase performance on low-stakes cognitive tests. Invoking racial stereotypes can affect test performance (Steele and Aronson 2005). Measures of children's non-cognitive skills that are based on teacher and parent reports of externalizing behavior, lying, or the child's ability to maintain focus on an assigned task are likely to be much more sensitive than cognitive test results to incentives, expectations, and peer effects. Particularly problematic is the interpretation of differences in test scores or behavior between children from high- and low-income families as pure differences in skills, when their environments are likely to vary substantially.

Borghans et al. (2011) focus on the problem of identifying traits from observed behavior, noting that behavior is influenced by incentives and by multiple traits. Incentives, in particular, may vary systematically by groups in the population defined over income, race, or gender. The task performance of individual i in group j, Y_{ij}, will depend on their level of skill, θ_i, and their chosen level of effort, e_i. Measuring skills on the basis of task performance requires that we control for effort, which is usually unobservable. There are a couple of ways that group membership can enter this process of inferring skills from observed performance. One possible source of group dependence is that the mapping of skill and effort into performance, φ_j, may vary by groups if, for example, teacher assessments are biased. Alternatively, the choice of effort will depend both on an individual effort endowment ($\bar{e}_i$) and incentives (p_{ij}) that may have a group-specific component (such as social sanctions against behavior that does not conform to gender norms)

$$Y_{ij} = \varphi_j(\theta_i, e_i)$$

$$e_i = f(\bar{e}_i, p_{ij}).$$

There may also be important environmental drivers of task performance, such as the intensity of other demands on a person's capabilities. An individual's reserves of self-control can be depleted by exertions of control (Muraven and Baumeister 2000). Experiments have shown that resisting temptation leads to a weakened ability to resist subsequent temptations, and individuals who have to cope with stressors such as noise and crowding are less able to delay gratification. Mani et al. (2013) find that poverty appears to degrade cognitive functioning. The farmers in their study exhibit diminished cognitive functioning before the harvest, when they are poor, compared to after the harvest, when they are rich. The differences are not accounted for by nutrition or work effort, and appear to be due to poverty-related demands on mental resources. Poor children, who are likely to face more chaotic and stressful conditions at home, may be less able to muster the resources to maintain focus and control at school, even if their fundamental capabilities are identical to those of other children.

Children with identical levels of a trait such as self-control may also have different expectations about the payoffs to exerting control, and in fact these payoffs may be dependent on context. In a variant of the marshmallow test, researchers preceded the classic test with two sessions in which randomly assigned children were primed to believe that their environment was reliable or unreliable (promised art supplies either did or did not show up). Children who had been exposed to the unreliability of the experimenters' promises scored substantially worse on the marshmallow gratification delay test (Kidd, Palmeri, and Aslin 2013). The researchers conclude that differences in performance on the marshmallow test may be due, not just to differences in self-control capabilities, but also to experiences about the reliability of the children's environments.

The return to noncognitive skills, in particular, seems to be highly context-dependent, and evidence of heterogeneity in returns is beginning to emerge. The positive association between a child's externalizing behavior and adult earnings that Papageorge, Ronda, and Zheng (2017) report does not extend to individuals from disadvantaged backgrounds.[7] Lundberg (2013) finds that the relationship between personality traits and college graduation in the United States varies by socioeconomic status, with conscientiousness having a substantial payoff only for youth with highly educated mothers. Such heterogeneity in returns should affect investments in skills as individuals set marginal costs equal to expected marginal returns. In environments such as the unreliable marshmallow test, developing impulse control may not make much sense—when such skills are not rewarded, they are not likely to be reinforced.

If observed behaviors depend not just on skills, but also on context—via perceived payoffs, distractions, peer effects, or supportive surroundings—then difficulties arise in comparing noncognitive skills that rely on behavioral assessments across groups. Early behavior can predict later behavior either because of persistent traits/skills or because of correlated circumstances. On the other hand, as Kautz et al. (2015) point out, group disparities based on self-reports about behavioral tendencies and beliefs such as personality can be affected by reference bias, in that how you assess yourself and your behavior may depend on peer behavior or cultural norms. One way to proceed is to compare alternative indicators of the same underlying skill.

7. Note that there are two ways to interpret this result: one, as true heterogeneity in the results to skill, or two, as instability in the mapping from skills to behavior across socioeconomic groups.

6.4.1 Male Impulsivity and Crime

Self-control is fundamental to many conceptualizations of noncognitive skill, as the marshmallow tests illustrate, and crime is thought to be strongly associated with deficits in self-control. The criminology literature links early difficulties in self-regulation and a failure to consider long-term consequences with later criminal behavior (Gottfredson and Hirschi 1990; Wright et al. 1999). The Add Health data includes several early indicators of impulsivity or low self-control that permit us to compare how well different measures predict later criminal behavior.

In the first wave of the study, when the Add Health subjects are in middle school or the early years of high school, three possible measures of impulsivity are collected that correspond to three of the basic types of noncognitive skill data: self-assessment, administrative records, and observed behavior:

- Self-assessment: "When making decisions, you usually go with your 'gut feeling' without thinking too much about the consequences of each alternative." The youth is classified as impulsive if he or she responds "agree" or "strongly agree" to this question.
- (Potential) administrative data: "Have you ever received an out-of-school suspension from school?" Since the majority of school suspensions are reported to be due to either disobedience or disruptive/disrespectful behavior, suspensions are likely to be strongly driven by individual impulsivity.
- Interviewer remarks: "Did the respondent ever seem bored or impatient during the interview?"

These three measures of impulsivity are positively, but not very strongly, correlated, with the strongest correlation being 0.12 between the self-assessment and report of school suspensions.

In Wave IV, when the subjects are age twenty-six to thirty-two, several measures of criminal activity and criminal justice contact are collected. These include an indicator for ever having been arrested, and reports of whether, in the past twelve months, the individual has deliberately damaged property, gotten involved in a physical fight, used or threatened to use a weapon, hurt someone so badly they needed medical care, or used a weapon or engaged in any other crime, including theft and selling drugs. Means of the impulsivity and crime measures for the male respondents are reported in table 6.4.

Predictive power is often used in noncognitive skill studies as evidence in support of the interpretation of a behavioral outcome as a valid skill measure. Kautz et al. (2015), for example, cite studies showing that behavioral measures are at least as good at predicting crime as self-reported psychologi-

Table 6.4 **Means of early impulsivity and later crime indicators, men (National Longitudinal Study of Adolescent to Adult Health)**

Impulsivity measures, Wave I	
Self-reported impulsivity	0.40
School suspension	0.35
Interviewer report	0.14
Self-reported crime and arrests, Wave IV	
Crime (in past 12 months)	0.31
Ever arrested	0.41

cal scales and conclude that behaviors can be used to infer a skill "as long as the measurement accounts for other skills and aspect of the situation." Table 6.5 reports results for linear probability models of impulsivity effects on crime and arrests (the patterns are similar if we use indicators of specific categories of crime). All three impulsivity indicators predict crime and arrests, with school suspensions having the strongest effect. When all impulsivity measures are included in the models (columns [4] and [8]), interviewer reports of impatience no longer has a significant association with crime. The inclusion of family background variables such as mother's education and family structure reduce the impulsivity coefficients by about 9 percent. Since school suspensions are most often triggered by disruptive behavior that suggests low self-regulation, it is plausible that they will be strongly predictive of future crime and criminal justice system contact.

Does this mean that a record of school suspensions is the best measure of crime-related impulsivity that is available in the Add Health study? What we should be looking for is a measure of capabilities that is not also a proxy for other factors driving behavior (such as incentives). In this respect, suspensions are a problematic measure of impulsivity. Table 6.6 reports the results from regressions that use other measures of noncognitive skills, family background, and race to predict the three measure of impulsivity. Both suspensions and the self-report are correlated with personality traits, but only suspensions are strongly related to mother's education. Most striking is the result that being black increases school suspensions by 50 percent, but does not change self-reported impulsivity and has a modest positive impact on interviewer reports of restlessness. In the racial dimension, other factors that drive behavior or school discipline are clearly relevant—school quality, racial bias in teacher and school responses to behavior, or even different expectations about the rewards of restraint in school are likely to be relevant. Clearly, race is an "aspect of the situation" that can be controlled for, but we are unlikely to be able to control consistently for home and neighborhood characteristics that affect behavior and drive this group discrepancy. Behavioral outcomes that depend on expected rewards, beliefs, other demands on a student's capabilities, or differential treatment by teachers and other

Table 6.5 **Effects of Wave I impulsivity on Wave IV crime and arrests, men (National Longitudinal Study of Adolescent to Adult Health)**

	Crime				Ever arrested			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Self-reported impulsivity	**.0477*** **				**.1074*** **			
	(0.0116)				**(0.0123)**			
+ family background	**.0443*** **			**.0354*** **	**.0971*** **			**.0704*** **
	(0.0116)			**(0.0117)**	**(0.0122)**			**(0.0120)**
School suspension		**.0970*** **				**.2710*** **		
		(0.0119)				**(0.0123)**		
+ family background		**.0879*** **		**.0842*** **		**.2497*** **		**.2389*** **
		(0.0122)		**(0.0123)**		**(0.0126)**		**(0.0127)**
Interviewer report			**.0373** **				**.0738** **	
			(0.0165)				**(0.0177)**	
+ family background			**.0357** **	.0255			**.0692** **	**.0433** **
			(0.0165)	(0.0166)			**(0.0175)**	**(0.0171)**

Note: Family background variables include mother's education and a dummy variable for living with both parents in Wave I.

***Significant at the 0.1 percent level.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

Table 6.6 Predicting Wave I measures of impulsivity, men (National Longitudinal Study of Adolescent to Adult Health)

	Self-reported impulsivity (1)	School suspension (2)	Interviewer report (3)
African American	.0088	**.1748*** **	**.0230** **
	(0.0153)	(0.0143)	(0.0108)
Lived with both parents	**−.0390*** **	**−.1238*** **	−.0030
	(0.0124)	(0.0116)	(0.0087)
Mother high school	.0133	**−.0645*** **	−.0187
	(0.0177)	(0.0165)	(0.0125)
Mother some college	−.0110	**−.0729*** **	−.0193
	(0.0204)	(0.0191)	(0.0144)
Mother college graduate	−.0311	**−.1664*** **	**−.0320** **
	(0.0196)	(0.0183)	(0.0138)
Personality			
Openness	**−.0465*** **	**−.0219*** **	−.0070
	(0.0064)	(0.0060)	(0.0045)
Conscientiousness	−.0084	**−.0104* **	.0036
	(0.0063)	(0.0059)	(0.0045)
Extraversion	**.0272*** **	**0.309*** **	**.0090* **
	(0.0063)	(0.0059)	(0.0045)
Agreeableness	**−.0181*** **	**−.0340*** **	**−.0180*** **
	(0.0064)	(0.0060)	(0.0046)
Neuroticism	**.0360*** **	**0.0533*** **	.0022
	(0.0067)	(0.0061)	(0.0046)
Observations	6,577	6,599	6,605
Adjusted R^2	0.024	0.091	0.004

Note: Standard errors in parentheses.
***Significant at the 0.1 percent level.
**Significant at the 1 percent level.
*Significant at the 5 percent level.

authorities are going to generate flawed measures of skill disparities across socioeconomic groups.

6.5 Noncognitive Human Capital and Growth

The case for broadening the concept of human capital to include noncognitive skills is a strong one. Many studies have shown that enriched environments in early childhood lead to positive outcomes later in life beyond their influence on measured cognitive skills, but evidence of the impact of education (or educational quality) on noncognitive skills is only beginning to emerge. Some personality traits are associated with positive outcomes in education and the labor market, though returns appear to vary by socioeconomic status (education) and occupation (earnings). Measures of adolescent emotional and behavioral problems, though they are not strongly predictive of labor market outcomes conditional on education, do have strong associations with educational attainment.

Some interesting issues to explore in future research on noncognitive skills concern possible complementarities between skills in educational and production processes. Noncognitive skills such as attention and self-control can increase the productivity of educational investments. Disruptive behavior and crime impose negative externalities in schools and communities that increased levels of some noncognitive skills could ameliorate. Aizer (2008) shows that diagnosis and treatment of attention deficit disorder (ADD) improves classroom peer behavior, which in turn increases student achievement. To indulge in pure speculation, it may be that broad improvements in noncognitive skills could have positive effects on technological innovation if these skills improve institutional quality and levels of cooperation within institutions.

To date, however, the state of our knowledge about the production of and returns to noncognitive skills is rather rudimentary. We lack a conceptual framework that would enable us to consistently define multidimensional noncognitive skills, and our reliance on observed or reported behavior as measures of skill make it impossible to reliably compare skills across groups that face different environments. Finally, there is increasing evidence that the returns to noncognitive skills may be highly context-dependent, a factor that limits our ability to extract policy recommendations from the existing literature.

References

Achenbach, Thomas M., and C. Edelbrock. 1981. *Child Behavior Checklist*. Burlington: University of Vermont.

Aizer, Anna. 2008. "Peer Effects and Human Capital Accumulation: The Externalities of ADD." NBER Working Paper no. 14354, Cambridge, MA.

Almlund, Mathilde, Angela Lee Duckworth, James J. Heckman, and Tim D. Kautz. 2011. "Personality Psychology and Economics." In *Handbook of the Economics of Education*, vol. 4, edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann, 1–182. Amsterdam: Elsevier Science.

Anger, Silke. 2012. "Intergenerational Transmission of Cognitive and Noncognitive Skills." In *From Parents to Children: The Intergenerational Transmission of Advantage*, edited by John Ermisch, Markus Jäntti, and Timothy Smeeding, 393–421. New York: Russell Sage Foundation.

Becker, Anke, Thomas Deckers, Thomas Dohmen, Armin Falk, and Fabian Kosse. 2012. "The Relationship between Economic Preferences and Psychological Personality Measures." *Annual Review of Economics* 4:453–78.

Borghans, Lex, Bart H. H. Golsteyn, James Heckman, and John Eric Humphries.

2011. "Identification Problems in Personality Psychology." *Personality and Individual Differences* 51 (3): 315–20.
Borghans, Lex, Huub Meijers, and Bas ter Weel. 2008. "The Role of Noncognitive Skills in Explaining Cognitive Test Scores." *Economic Inquiry* 46 (1): 2–12.
Bouchard Jr., Thomas J., and John C. Loehlin. 2001. "Genes, Evolution, and Personality." *Behavior Genetics* 31 (3): 243–73.
Bowles, Samuel, and Herbert Gintis. 1976. *Schooling in Capitalist America: Educational Reform and the Contradictions of American Life*. New York: Basic Books, Inc.
Bowles, Samuel, Herbert Gintis, and Melissa Osborne. 2001. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39 (4): 1137–76.
Cadena, Brian, and Benjamin Keys. 2015. "Human Capital and the Lifetime Costs of Impatience." *American Economic Journal: Economic Policy* 7 (3): 126–53.
Chetty, Raj, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan. 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star." *Quarterly Journal of Economics* 126 (4): 1593–660.
Cobb-Clark, Deborah. 2015. "Locus of Control and the Labor Market." IZA Discussion Paper no. 8678, Institute for the Study of Labor.
Cobb-Clark, Deborah, Marco Caliendo, and Arne Uhlendorff. 2015. "Locus of Control and Job Search Strategies." *Review of Economics and Statistics* 97 (1): 88–103.
Cunha, Flavio, and James J. Heckman. 2008. "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Journal of Human Resources* 43 (4): 738–82.
Currie, Janet. 2011. "Inequality at Birth: Some Causes and Consequences." *American Economic Review* 101 (3): 1–22.
Datta Gupta, Nabanita, Mette Lausten, and Dario Pozzoli. 2012. "Does Mother Know Best? Parental Discrepancies in Assessing Child Functioning." IZA Discussion Paper no. 6962, Institute for the Study of Labor.
Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132 (4): 1593–640.
Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. 2010. "Are Risk Aversion and Impatience Related to Cognitive Ability?" *American Economic Review* 100 (3): 1238–60.
Duncan, Greg J., and Katherine Magnuson. 2011. "The Nature and Impact of Early Achievement Skills, Attention Skills, and Behavior Problems." In *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*, edited by Greg J. Duncan and Richard J. Murnane. New York: Russell Sage Foundation.
———. 2013. "Investing in Preschool Programs." *Journal of Economic Perspectives* 27 (2): 109–32.
Filer, Randall K. 1986. "The Role of Personality and Tastes in Determining Occupational Structure." *Industrial & Labor Relations Review* 39 (3): 412–24.
Gertler, Paul, James Heckman, Rodrigo Pinto, Arianna Zanolini, Christel Vermeersch, Susan Walker, Susan M. Chang, and Sally Grantham-McGregor. 2014. "Labor Market Returns to an Early Childhood Stimulation Intervention in Jamaica." *Science* 344 (6187): 998–1001.
Goldberg, Lewis R. 1981. "Language and Individual Differences: The Search for Universals in Personality Lexicons." In *Review of Personality and Social Psychology*, vol. 2, edited by Ladd Wheeler, 141–65. Thousand Oaks, CA: Sage.

Gottfredson, Michael R., and Travis Hirschi. 1990. *A General Theory of Crime*. Stanford, CA: Stanford University Press.
Hanushek, Eric A., and Dennis D. Kimko. 2000. "Schooling, Labor-Force Quality, and the Growth of Nations." *American Economic Review* 90 (5): 1184–208.
Hanushek, Eric A., and Ludger Woessmann. 2008. "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature* 46 (3): 607–68.
Heckman, James J., Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes." *American Economic Review* 103 (6): 1–35.
Heckman, James J., and Yona Rubinstein. 2001. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program." *American Economic Review* 91 (2): 145–49.
Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3): 411–82.
Heineck, Guido. 2011. "Does It Pay to Be Nice? Personality and Earnings in the United Kingdom." *Industrial & Labor Relations Review* 64 (5): 1020–38.
Heineck, Guido, and Silke Anger. 2010. "The Returns to Cognitive Abilities and Personality Traits in Germany." *Labour Economics* 17 (3): 535–46.
Kautz, Tim, James J. Heckman, Ron Diris, Bas ter Weel, and Lex Borghans. 2015. "Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success." OECD Education Working Paper no. 110, OECD Publishing.
Kidd, Celeste, Holly Palmeri, and Richard N. Aslin. 2013. "Rational Snacking: Young Children's Decision-Making on the Marshmallow Task Is Moderated by Beliefs about Environmental Reliability." *Cognition* 126 (1): 109–14.
Krueger, Alan B., and David Schkade. 2008. "Sorting in the Labor Market: Do Gregarious Workers Flock to Interactive Jobs?" *Journal of Human Resources* 43 (4): 859–83.
Lindqvist, Erik, and Roine Vestman. 2011. "The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment." *American Economic Journal: Applied Economics* 3 (1): 101–28.
Lundberg, Shelly. 2012. "Personality and Marital Surplus." *Journal of Labor Economics* 1 (1): 1–21.
———. 2013. "The College Type: Personality and Educational Inequality." *Journal of Labor Economics* 31 (3): 421–41.
———. 2015. "Skill Disparities and Unequal Family Outcomes." *Research in Labor Economics* 41:177–212.
Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. "Poverty Impedes Cognitive Function." *Science* 341 (6149): 976–80.
Mischel, Walter, Ebbe B. Ebbesen, and Antonette Raskoff Zeiss. 1972. "Cognitive and Attentional Mechanisms in Delay of Gratification." *Journal of Personality and Social Psychology* 21 (2): 204–18.
Mueller, Gerrit, and Erik Plug. 2006. "Estimating the Effect of Personality on Male and Female Earnings." *Industrial & Labor Relations Review* 60 (1): 3–22.
Muraven, Mark, and Roy F. Baumeister. 2000. "Self-Regulation and Depletion of Limited Resources: Does Self-Control Resemble a Muscle?" *Psychological Bulletin* 126 (2): 247–59.
Nandi, Alita, and Cheti Nicoletti. 2014. "Explaining Personality Pay Gaps in the UK." *Applied Economics* 46 (26): 3131–50.
Nyhus, Ellen K., and Empar Pons. 2005. "The Effects of Personality on Earnings." *Journal of Economic Psychology* 26 (3): 363–84.

Papageorge, Nicholas W., Victor Ronda, and Yu Zheng. 2017. "The Economic Value of Breaking Bad: Misbehavior, Schooling and the Labor Market." IZA Discussion Paper no. 10822, Institute for the Study of Labor.
Rustichini, Aldo, Colin G. DeYoung, Jon C. Anderson, and Stephen V. Burks. 2012. "Toward the Integration of Personality Theory and Decision Theory in the Explanation of Economic and Health Behavior." IZA Discussion Paper no. 6750, Institute for the Study of Labor.
Segal, Carmit. 2012. "Working When No One Is Watching: Motivation, Test Scores, and Economic Success." *Management Science* 58 (8): 1438–57.
———. 2013. "Misbehavior, Education, and Labor Market Outcomes." *Journal of the European Economic Association* 11 (4): 743–79.
Shonkoff, Jack P., Andrew S. Garner, Benjamin S. Siegel, Mary I. Dobbins, Marian F. Earls, Laura McGuinn, John Pascoe, and David L. Wood. 2012. "The Lifelong Effects of Early Childhood Adversity and Toxic Stress." *Pediatrics* 129 (1): e232–46.
Steele, Claude M., and Joshua Aronson. 2005. "Stereotypes and the Fragility of Academic Competence, Motivation, and Self-Concept." In *Handbook of Competence and Motivation*, edited by Andrew J. Elliot and Carol S. Dweck, 436–55. New York: Guilford Press.
Weiss, Andrew. 1988. "High School Graduation, Performance, and Wages." *Journal of Political Economy* 96 (4): 785–820.
World Bank. 2015. "World Development Report 2015: Mind, Society, and Behavior." Washington, DC, World Bank. https://doi.org/10.1596/978-1-4648-0342-0.
Wright, Bradley R. Entner, Avshalom Caspi, Terrie E. Moffitt, and Phil A. Silva. 1999. "Low Self-Control, Social Bonds, and Crime: Social Causation, Social Selection, or Both?" *Criminology* 37 (3): 479–514.

Comment David J. Deming

Shelly Lundberg has written an important chapter about the rapidly growing study of "noncognitive" skills in economics. This chapter should be required reading for social scientists who seek to use measures of noncognitive skills in schools and other educational settings to make important policy decisions. I largely agree with her conclusions about the state of the literature, which I summarize crudely as follows. Although the evidence is overwhelming that so-called noncognitive skills are important predictors of many important life outcomes, we do not really agree on what they are (and importantly, what they are not). Thus we have very little idea of how to measure noncognitive skills well, and even less idea of how to use measures of noncognitive skills to make high-stakes policy decisions.

David J. Deming is professor of public policy at the Harvard Kennedy School, professor of education and economics at the Harvard Graduate School of Education, and a research associate of the National Bureau of Economic Research.
For acknowledgments, sources of research support, and disclosure of the author's material financial relationships, if any, please see http://www.nber.org/chapters/c13702.ack.