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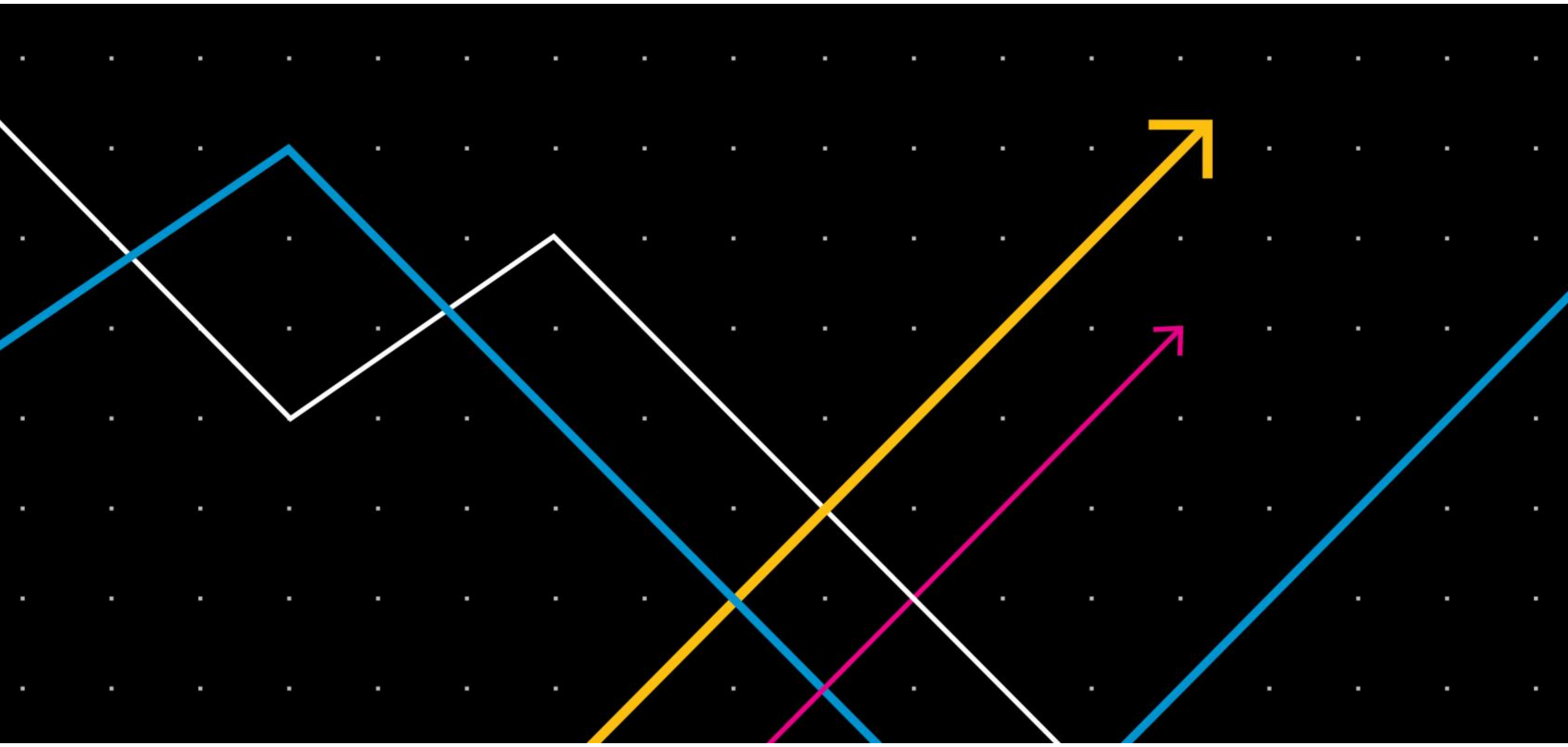

RESEARCH REPORT

What Evidence Could Help Schools Put Students on a Path to Economic Mobility?

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Putting Students on a Path to Economic Mobility

Upward mobility is core to the American dream but remains elusive for many, a problem that harms individuals and society at large.[1] Education is widely viewed as a key lever to support students' upward mobility, but there is too little actionable information about how schools promote lifelong success.[2] As a result, PK–12 education tends to focus on conventional indicators of success, such as scores on math and reading tests, that are important but are unlikely to capture the full set of skills and competencies that drive upward mobility.

For educators and policymakers to take actions that bolster students' upward mobility, they cannot experiment and then wait 10 to 20 years for results. Instead, they need to know which skills and competencies within their sphere of influence they should target. For example, how much should they focus on teaching math skills (and which specific ones), fostering students' self-management abilities, or developing teamwork skills?

This report reviews the available evidence on the direct links between PK–12 education and economic mobility, including correlational studies that identify PK–12 skills and competencies that predict economic success and the more limited set of causal studies that help reveal which skills and competencies truly drive upward mobility. We focus on studies that directly analyze relationships between PK–12 measures and labor market outcomes, noting that an important related literature addresses intermediate steps in the causal chain from high school to postsecondary education to the labor market.[3]

We find that the available research offers little guidance about which skills and competencies in PK–12 education are most important for economic success. Not many studies connect students' PK–12 experiences to their economic success as adults, and the existing research defines success narrowly in terms of wages, ignoring other dimensions such as finding dignity in one's work and a sense of autonomy in life and belonging in one's community (Acs et al. 2018).

The available evidence also makes insufficient space for the interplay between individual-level and broader structural factors that affect children's readiness to learn, the functioning of school systems, and how success in school translates into longer-term success. Some research examines how PK–12 factors function differently across different groups of students (e.g., by race or ethnicity and gender), but few seek to understand why patterns differ or how they intersect with broader factors. For example, does social capital matter more (or matter less) in areas with higher levels of school segregation or labor market discrimination? Do racism and other forms of oppression (both historical and current) result in the answer to this question being different for Black students than for white students?

A key limitation of most available studies is that they rely on PK–12 measures collected for research purposes rather than those used in the regular course of schooling. Several studies linking math and reading skills to earnings use tests the armed forces developed decades ago rather than the kinds of assessments that are in regular use in schools today. And studies of "noncognitive" factors such as self-esteem and self-control often rely on decades-old survey measures that are not widely used in schools. These gaps in the available evidence limit its applicability to those working in PK–12 settings.

In light of the chasm between the evidence that is available and the evidence that is needed to support educators and policymakers seeking to increase upward mobility, we argue that a new generation of research at the intersection of PK–12 education and economic mobility is needed. This research should seek to understand the PK–12 skills and competencies that drive upward mobility, how measures of these skills and competencies function across different people and places, and how they intersect with broader factors both within and beyond education.

In what follows, we first discuss a fundamental shortcoming in the questions asked in the existing literature and how they are answered—namely, inquiries into the connection between education and long-term success tend to disregard the complex interplay between individuals and the systems and structures they are a part of. From there, we discuss what we know about skills and competencies that correlate and potentially drive mobility, with particular attention paid to the gaps in this literature that make it less than actionable for education policymakers and practitioners. We close with longer-term directions for education-to-mobility researchers to pursue, as well as quicker wins they can act on immediately.

Individual Students Need to Be Understood within the Context of Broader Systems and Structures

This research synthesis focuses on the few studies that directly connect measures of individual students' PK–12 skills and competencies to their economic success as adults (defined in terms of wages in nearly all the studies). But economic mobility, though experienced at the individual level, is the result of broader systems and structures both in and beyond the education context. And these factors, which are often rooted in racism, classism, sexism, and other forms of oppression (both historical and current), can play out differently for individuals of different intersectional identities.

Three categories of broader or contextual factors exist at multiple scales (from the household, to the neighborhood, to the city, and beyond) and help illustrate the distinct and overlapping ways they can shape both success in school and upward mobility.[4] We do not attempt to review the full body of available research on these factors, but we provide examples to demonstrate that focusing on individual factors and behaviors when seeking to understand and advance economic mobility is flawed and leads to interventions that, at best, are unsuccessful and inefficient and, at worst, feed inequities and harmful narratives of why they persist (Deich, Fedorowicz, and Turner 2022).[5]

The first category includes nonschool factors that shape children's readiness to learn. These are akin to the social determinants of health and are sometimes described as the social determinants of learning (Levinson and Cohen 2023). Factors that are negatively linked to children's ability to succeed at school include childhood maltreatment (Jacob and Ryan 2018), poor health (Currie et al. 2010), and food insecurity (Hines, Markowitz, and Johnson 2021). Jebb, Brown-Hunt, and Duckworth (forthcoming) recently developed a 10-item "necessities index" that considers these and other basic needs, such as transportation, safety, housing, and academic and social support.

These nonschool factors can intersect to create barriers for students. For example, substandard housing alone is a stressor that affects education (Coley, Lynch, and Kull, n.d.). But substandard housing can also mean exposure to environmental toxins that cause brain damage and behavioral problems that affect education outcomes. And high housing costs (or needed repairs) may strain scarce financial resources that reduce what families can spend on food, health care, or education for their children.

The second category includes factors that affect the functioning of schools and school systems. A few studies have directly linked some of these factors to students' economic outcomes. Equalizing school funding across school districts leads to increased adult earnings and economic mobility, especially for children from low-income families (Biasi 2023; Jackson, Johnson, and Persico 2016; Rothstein and Schanzenbach 2022). School desegregation and the increases in school quality that came with it increased adult earnings for Black students, with no effects on white students (Johnson 2011).

Other examples of factors in this category include teacher labor markets, student assignment policies (including attendance boundaries and choice policies), and how police are deployed in schools. The category also includes structures beyond school systems that nonetheless affect how schools operate. For example, residential segregation has clear links to school segregation, and income distributions (and tax policies) have implications for school funding levels (and distributions).

The third category comprises factors that undermine or boost how success in school translates into long-term success. A student can do everything right but still struggle to succeed in the labor market because of discrimination, a lack of high-quality jobs, inadequate health care, or other factors. Differences in economic mobility across places within the US have been linked to income inequality, family structure, social capital, economic connectedness, and labor market policies (Chetty, Friedman, and Rockoff 2014; Chetty et al. 2022a, 2022b; Rothstein 2019).

Contextual factors can span these categories, with multiple mechanisms linking them to students' upward mobility. For example, residential segregation can affect students' readiness to learn (e.g., disinvested neighborhoods expose students to environmental toxins and crime), the functioning of school systems (e.g., by increasing concentrated poverty), and how school success translates into long-term outcomes (e.g., by increasing commute times to high-quality jobs).

Situating individual students and families within broader systems and structures is crucial to interpreting both existing studies connecting education to economic mobility and designing the next generation of research. Some of the research we review examines how correlations between PK–12 factors and adult wages vary by student factors such as race or ethnicity, gender, and income. But most studies that look at heterogeneity of effects by socioeconomic factors such as race fail to include a historical, systemic, and structural discussion of why any differences may exist. Much of the existing literature comes from economics and other social sciences using similar quantitative methods, which speaks to the need to increase the contextual and structural skills of those already studying the education-to-mobility space, as well as the need for new perspectives, disciplines, and methodologies.

Math and Reading Scores Consistently Predict Future Earnings

The shortcomings of the existing literature notwithstanding, we do know some things about the skills and competencies that link to wage-based definitions of upward mobility. A substantial body of evidence establishes a fairly consistent correlation between measures of math and reading skills and adult earnings, but these studies typically do not distinguish between the predictive power of tests of different kinds of academic skills, nor do they draw on data about the kinds of achievement tests US schools use today. As a result, the studies' implications for PK–12 educators and policymakers seeking to understand the skills and competencies within their purview that predict future economic success are unclear.

An early body of research, mostly by labor economists, sought to understand how “cognitive skills” (also called “ability” or, in earlier research, “IQ”) related to labor market outcomes. Studies examined questions such as how those relationships change, how they are moderated by factors such as educational attainment and “noncognitive” factors, and the degree to which they account for differences in earnings by gender and race or ethnicity (Zax and Reese 2002).

These studies draw on nationally representative datasets, such as the National Longitudinal Study of Youth 1979 (NLSY79) and its later 1997 version.[6] For example, Lin, Lutter, and Ruhm (2018) found that adolescents who scored higher on a battery of literacy and math tests in 1997 tended to earn more in their twenties (controlling for student and family demographics), and this relationship strengthened from age 22 to age 29. Specifically, a 1 standard deviation increase in scores corresponded to a 13 percent increase in earnings at age 24 and a 23 percent increase at age 29.[7]

Murnane and coauthors (2000) calculated the correlation between scores on a test of basic math skills (e.g., fractions, decimals, and line graphs) at the end of high school and earnings about 10 years later.[8] Their estimates imply that, among high school seniors in 1982, a 1 standard deviation increase in math scores is associated with a 13 percent increase in annual earnings at age 27 for women and a 12 percent increase for men (controlling only for race or ethnicity).[9] The authors motivate their focus on math skills by noting preliminary analyses suggesting weaker relationships between reading scores and earnings.[10]

None of these studies use data from tests that are commonly used in education today. In a more recent study, Chetty and coauthors (2011) analyzed data from a disproportionately low-income set of Tennessee schools in the 1980s. As part of the study, students in grades K–3 took the Stanford Achievement Test, a multiple-choice test of math and reading that is closer to but still distinct from the tests states use today. The authors find that a 1 standard deviation increase in tests scores (combined across math and reading) is associated with an 18 percent increase in earnings at age 27, controlling for student and family characteristics (including parents’ income).

The most relevant study connecting PK–12 achievement to adult earnings is Chetty, Friedman, and Rockoff's (2014) analysis of state-administered tests given to students in grades 3–8 in a large urban district that they linked to earnings records from tax data. The authors find that a 1 standard deviation increase in math and English scores is associated with a 36 percent increase in earnings. Controlling for student, teacher, and class characteristics, including test scores from the prior year, reduces this association to 12 percent.

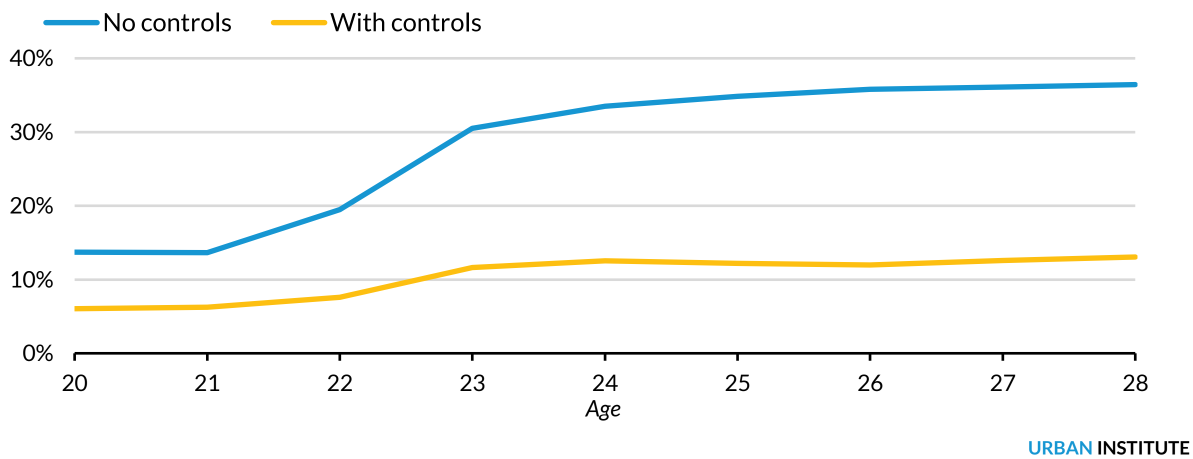
The results without controls tell us that this state-administered test was a very strong predictor of adult earnings. The results with controls (including students' scores in the prior year) indicate this relationship partly reflects how much a student learned in a given year. At the same time, contextual factors at the student, classroom, and school levels account for a large portion of the relationship.[11]

This study also shows how the predictive power of math and reading scores (with controls) varies by subject, age when earnings are measured, and student characteristics. The authors report that math scores are modestly stronger predictors of earnings, with a 1 standard deviation increase corresponding to 14 percent higher earnings, compared with 10 percent for English scores. The authors also show how the predictive strength of test scores increases through students' early adulthood and then levels off in their late twenties (figure 1).

FIGURE 1

The Correlation of Math and English Scores with Earnings Increases with Age

Percentage increase in earnings associated with a 1 standard deviation increase in grades 4–8 math and English scores, by age



Source: Raj Chetty, John N. Friedman, and Jonah E. Rockoff, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review* 104, no. 9 (2014): 2633–79, https://doi.org/10.1257/aer.104.9.2633, appendix table 4.

Looking at heterogeneity by student characteristics, Chetty, Friedman, and Rockoff (2014) find that, across all these groups, a 1 standard deviation increase in scores is associated with about a $2,500 increase in earnings (including a rich set of controls). But average earnings vary across many of these groups (suggesting the importance of contextual factors), resulting in different percentage changes: 15 percent for Black and Hispanic students compared with 8 percent for students of other races or ethnicities, and 14 percent for students with lower-income parents compared with 10 percent for higher-income parents. Differences by gender are smaller: 13 percent for girls versus 11 percent for boys.

TABLE 1

Several Studies Connect Math and Reading Scores to Adult Earnings

Sample	Test used and statistical controls	Predicted increase in earnings associated with 1 standard deviation change in test score	Source
US high school seniors in 1982 (born around 1964)	Basic math skills, controlling for race or ethnicity	Women at age 27: 13 percent Men at age 27: 12 percent	Murnane et al. (2000)[a]
US adolescents ages 12 to 16 in 1996 (born 1980 to 1984)	Four tests used by armed services (i.e., word knowledge, paragraph comprehension, math knowledge, and arithmetic reasoning), controlling for student and family characteristics[b]	Age 24: 13 percent Age 29: 23 percent	Lin, Lutter, and Ruhm (2018)[c]
Students in grades K–3 at 79 schools in Tennessee in 1985–88 (born around 1980)	Multiple-choice math and reading tests, controlling for student and parent characteristics[d]	18 percent at age 27	Chetty et al. (2011)[e]
Students in grades 4–8 in a large urban district in 2001–05 (born 1987 to 1991)[f]	State end-of-year tests in math and reading, controlling for prior scores and student, teacher, and class characteristics[g]	Without controls: 36 percent at age 27 With controls: 12 percent at age 27	Chetty, Friedman, and Rockoff (2014)[h]

[a] Richard J. Murnane, John B. Willett, Yves Duhaldeborde, and John H. Tyler, "How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?" *Journal of Policy Analysis and Management* 19, no. 4 (2000): 547–68.

[b] The controls are student sex, race or ethnicity, foreign-born status, foreign language spoken at home, urban residence, parents' education, parents' foreign-born status, and number of siblings.

[c] Dajun Lin, Randall Lutter, and Christopher J. Ruhm, "Cognitive Performance and Labour Market Outcomes," *Labour Economics* 51 (April 2018): 121–35. https://doi.org/10.1016/j.labeco.2017.12.008.

[d] Chetty and coauthors (2011) note, "The parent characteristics are a quartic in parent's household income interacted with an indicator for whether the filing parent is ever married between 1996 and 2008, mother's age at child's birth, and indicators for parent's 401(k) savings and home ownership. The student characteristics are gender, race, age at entry-year entry, and free lunch status."

[e] Raj Chetty, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan, "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star," *Quarterly Journal of Economics* 126, no. 4 (2011): 1593–660, https://doi.org/10.1093/qje/qjr041.

[f] The authors restrict the sample to students born by 1991.

[g] Chetty, Friedman, and Rockoff (2014) note, "The student-level control vector…includes cubic polynomials in prior-year math and English scores, interacted with the student's grade level to permit flexibility in the persistence of test scores as students age. We also control for the following student level characteristics: ethnicity, gender, age, lagged suspensions and absences, and indicators for grade repetition, free or reduced-price lunch, special education, and limited English. The class-level controls…consist of the following elements: (1) class size and class-type indicators (honors, remedial), (2) cubics in class and school-grade means of prior-year test scores in math and English (defined based on those with non-missing prior scores) each interacted with grade, (3) class and school-year means of all the individual covariates…and (4) grade and year dummies." Teacher controls are teacher fixed effects.

[h] Raj Chetty, John N. Friedman, and Jonah E. Rockoff, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review* 104, no. 9 (2014): 2633–79, https://doi.org/10.1257/aer.104.9.2633.

In summary, several studies have examined the relationship between scores on math and reading (or English) tests in PK–12, and all of them have found that these scores predict earnings in adulthood. There is some evidence that math scores are more predictive than reading scores and that these correlations increase over the course of individuals' twenties (a period when some pursue college and graduate education).

But this body of research also has significant limitations from the perspective of those trying to understand how to use PK–12 achievement data to foster upward mobility. Only one study has used data from state-required standardized tests (and 2000s-era tests may differ from those in use today), and no studies have analyzed the data through a mobility lens or examined nonwage dimensions of upward mobility (though some have found a stronger relationship between achievement and earnings for children from lower-income families).

Additionally, studies seldom examine how much of a skill is "good enough" for future economic success, much less how answers to that question may vary based on the contextual factors, described above, that affect the translation of skills and competencies to value in the labor market and beyond. For example, having a reasonable level of reading comprehension may be important for achieving upward mobility, but being able to analyze complex texts may not add much on top of that. The one study that did look at the relationship with earnings across the test score distribution did not find evidence of such "nonlinearities" with kindergarten math and reading scores (Chetty et al. 2011).

Finally, the available evidence offers little guidance about which skills within math and reading (e.g., basic arithmetic, solving algebraic equations, interpreting data) are most predictive of earnings, and we are not aware of any studies connecting data on economic success to measures of skills in other subjects, such as science or social studies.

"Noncognitive" Factors Also Matter but Are Poorly Measured in PK–12 Education

It is widely understood that success in school and life is driven by more than just academic skills and knowledge. And this understanding is backed up by decades of research linking "noncognitive" factors to various outcomes, including earnings. These factors potentially affect economic mobility both directly (e.g., teamwork skills developed in adolescence are valued in the labor market) and indirectly (e.g., students with greater motivation learn more in school, which helps them succeed in the labor market).

“Noncognitive” is a misnomer because these skills are highly cognitive; other imperfect labels include personal qualities, character skills, social and emotional learning competencies, and soft skills (Duckworth and Yeager 2015).[12] The skills (some of which may be more accurately described as competencies, traits, or qualities) in this expansive category, which often overlap, include the following:

- the “Big 5” personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism
- self-esteem and self-efficacy
- self-control, self-management, motivation, grit, and growth mindset
- (mis)behavior (behaviors are often used as a measure of underlying skills)
- problem solving, critical thinking, curiosity, and creativity
- social skills and teamwork

Evidence indicates that many of these factors are malleable during children’s schooling years (Belfield et al. 2015; Borghans et al. 2008; Farrington et al. 2012), but research on how these skills are linked to economic outcomes is limited by its reliance on data collected for research purposes rather than the real world of PK–12 education. For example, it is unclear whether measures based on a one-time survey of students administered by researchers would function in the same way as data regularly collected by schools.

We are not aware of any studies that directly examine how these skills are related to upward mobility for students from lower-income families or that consider nonwage dimensions of mobility. For example, it is plausible that a child who builds self-esteem, grit, and growth mindset would be more likely to achieve greater autonomy as an adult, but we are unaware of any research that directly tests this hypothesis.

A large body of research by both psychologists and economists does establish correlations between many of these factors and the contemporaneous earnings of adults. For example, a 2021 meta-analysis of 62 articles linking the “Big 5” personality traits to earnings found that three of these traits (openness, conscientiousness, and extraversion) are associated with higher earnings, and the other two (agreeableness and neuroticism) are associated with lower earnings (Alderotti, Rapallini, and Traverso 2023). And Deming (2022) has documented the increasing economic returns to what he calls “higher-order” skills, such as problem solving and teamwork.

Studies that connect “noncognitive” measures from students’ PK–12 years to adult earnings are rarer. Labor economists have used representative datasets such as the NLSY79 to connect measures of self-esteem and “locus of control” collected from adolescents at ages 14 to 22 to their earnings as adults, finding that these measures predict higher earnings (Heckman, Stixrud, and Urzua 2006). An analysis that focused on just the NLSY79 participants who were in high school when they were initially tested confirmed that self-esteem positively predicts earnings at ages 27 and 28 for this group (Murnane et al. 2001).

Another dataset covering 10th-graders in 1990 found that student-reported measures of young men’s self-esteem and locus of control were positive correlated with their earnings at ages 26 and 27, and this relationship was stronger for men with lower earnings (the study did not analyze data for women) (Eren and Ozbeklik 2013).

The same data (on both men and women) were used in another study to show that teachers’ reports of student misbehavior in eighth grade (e.g., being tardy, absent, disruptive, inattentive, and not completing homework) were associated with lower earnings (Segal 2013). In both studies, the relationships between earnings and “noncognitive” measures were present even when controlling for math and reading scores.[13]

But one study found that certain types of misbehavior are associated with higher earnings. Papageorge, Ronda, and Zheng (2022) showed that teacher reports of students’ “externalizing behavior” (e.g., aggression and hyperactivity) were linked to higher wages in adulthood for both boys and girls, while other types of “internalizing” misbehavior (e.g., anxiety, depression, and shyness) predicted lower wages.

This study indicates that factors that are seen as detrimental in the PK–12 context can have a positive relationship with earnings. Papageorge and coauthors’ study is based primarily on data on UK children born in 1958, but the authors obtain broadly similar findings using US data that includes a more recent dataset (children born around 1975). Importantly, Papageorge and coauthors find that the labor market benefits of bad behavior may not extend to children who grew up in families of a low socioeconomic status, which raises “the concerning possibility that children from poorer families are unable to unleash the potential of skills that are valuable and lucrative for children born into wealthier families.” In other words, some combination of classism and racism is likely at play.

All these studies are based on “noncognitive” measures developed and implemented for research purposes, mostly decades ago. We are not aware of any studies linking “noncognitive” measures collected by schools or districts to earnings. This largely reflects the fact that, unlike the math and reading tests that have been administered in evolving forms for decades, “noncognitive” measures are not yet widely collected at scale or fed into student information systems (which are the primary source for the statewide data systems researchers often use).

An early leader in the collection of data on “noncognitive” factors is a group of California school districts called the CORE districts that have been measuring what they call “social-emotional learning competencies” since 2014. The competencies they selected are growth mindset, self-efficacy, self-management, and social awareness. This group of 8 districts serving more than a million students developed a data system now used by more than 100 additional California districts and charter schools (Gehlbach and Hough 2018; West et al. 2020).

Studies showed that the social-emotional measures used in the CORE districts appear to vary across schools and across classrooms within schools (Fricke et al. 2021; Meyer et al. 2019), that they vary across grades and demographic groups (West et al. 2020), and that changes in measures of these competencies predict changes in test scores and attendance (Kanopka et al. 2020). These data have not yet been linked to economic mobility outcomes such as adult earnings.

Chicago Public Schools has also been measuring social-emotional development among students in grades 6–12 using an annual survey since 2010–11 (Jackson et al. 2021). These kinds of efforts may become more common, given that many states have adopted social-emotional competencies as a guidance or framework. But the efforts have also become politicized in many places, which may slow or reverse this trend.[14]

In sum, research on “noncognitive” factors suggests they are a key potential driver of upward mobility but does not establish which factors matter most, for whom, and under what circumstances. There is suggestive evidence that the strength of the relationships between earnings and “noncognitive” factors varies more by contextual factors than the corresponding relationships with math and reading scores.[15]

Significantly advancing our knowledge will require developing a broader array of contextually situated measures of different “noncognitive” factors that can be implemented in PK–12 settings and, with time, connected to data on students’ economic mobility (including incomes) and broader factors. Duckworth and Yeager (2015) propose several potential paths to building beyond self-reported measures, including performance tasks and harnessing digital data on students’ learning behaviors.[16]

Correlation Is Not (Always) Causation: What Truly Drives Upward Mobility?

Educators and policymakers seeking to advance students' upward mobility need to know which measures of PK–12 skills and competencies are correlated with economic success and which truly drive mobility in a causal sense and are influenced by school systems. For example, it could be the case that students from higher-income families have higher test scores and income as adults, leading to a positive correlation between the two, but increasing test scores (e.g., by choosing a better curriculum) would not increase incomes because it was the availability of family resources (e.g., stable housing, tutoring, college tuition, or social networks) that was truly driving future success.

The ideal way to generate this kind of causal evidence on the drivers of upward mobility would be to run many randomized experiments in PK–12 education, collect data on many PK–12 skills and competencies (both academic and "noncognitive") that track the interventions' short-term impacts, and then wait long enough to collect data on earnings and other measures of mobility. The researcher could then measure the interventions' causal impacts on both short- and long-term measures and then test which short-term impacts were the most reliable predictors of the long-run impacts on upward mobility (and for whom and under what circumstances).[17]

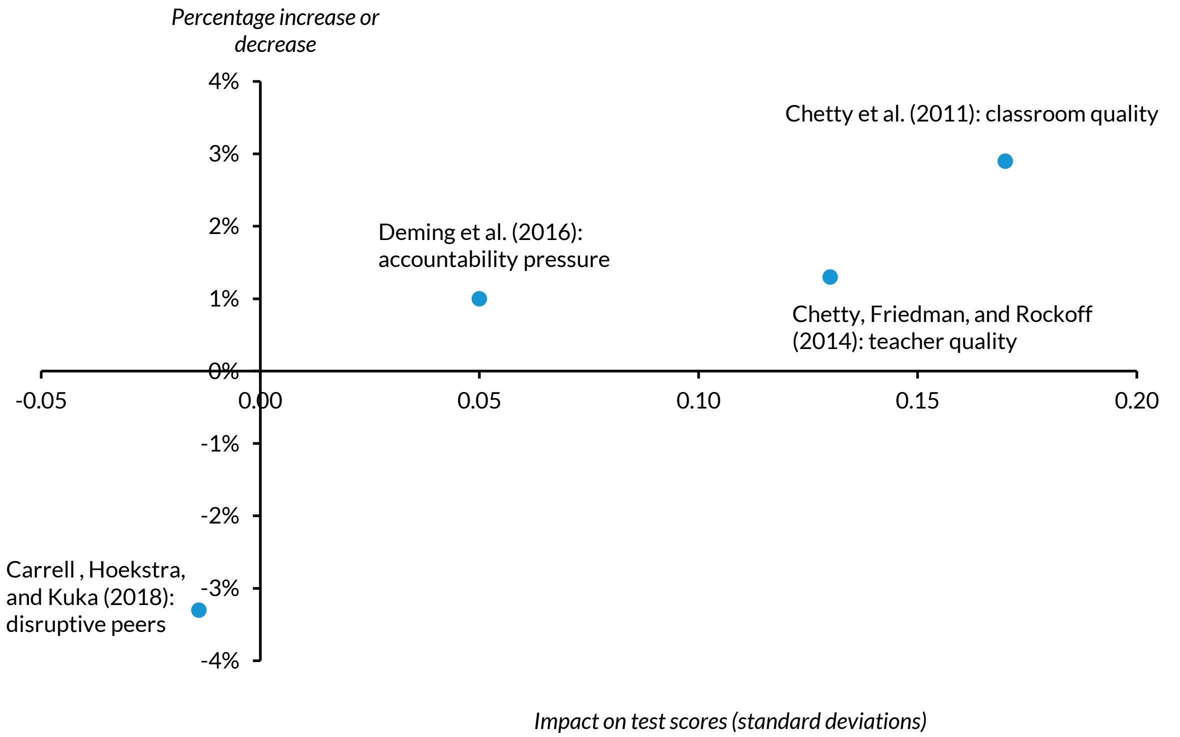
It is neither feasible nor ethical to run this kind of grand set of experiments, so in practice, we must rely on interventions and policies for which researchers have estimated both short-term impacts on PK–12 measures and long-run impacts on economic outcomes.[18] We identified only a handful of such studies, all of which used wages as the long-run outcome (we did not find any that examined nonwage dimensions of mobility).[19]

These five studies, summarized in table 2, use different methodologies and cover different student populations, complicating comparisons of results across studies. Figure 2 shows that, across four of the studies, impacts on test scores were roughly correlated with impacts on earnings. Three of the studies found earnings impacts of 10 to 20 percent per standard deviation increase in test scores (Chetty et al. 2011; Chetty, Friedman, and Rockoff 2014; Deming et al. 2016), which is broadly consistent with the correlational evidence reviewed above. The fourth study, of the impact of disruptive peers (proxied by classmates' exposure to domestic violence), found a relatively large earnings impact despite a small test score impact (Carrell, Hoekstra, and Kuka 2018).

FIGURE 2

Comparing Impacts on Test Scores and Earnings

Impact on earnings (percentage increase or decrease)



Sources: Scott E. Carrell, Mark Hoekstra, and Elira Kuka, "The Long-Run Effects of Disruptive Peers," *American Economic Review* 108, no. 11 (2018): 3377–415, https://doi.org/10.1257/aer.20160763; Raj Chetty, John N. Friedman, and Jonah E. Rockoff, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review* 104, no. 9 (2014): 2633–79, https://doi.org/10.1257/aer.104.9.2633; Raj Chetty, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan, "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star," *Quarterly Journal of Economics* 126, no. 4 (2011): 1593–660, https://doi.org/10.1093/qje/qjr041; and David J. Deming, Sarah Cohodes, Jennifer Jennings, and Christopher Jencks, "School Accountability, Postsecondary Attainment, and Earnings," *Review of Economics and Statistics* 98, no. 5 (2016): 848–62, https://doi.org/10.1162/REST_a_00598.

Chetty and coauthors (2011) and Chetty, Friedman, and Rockoff (2014) both found that the initial effects on test scores "faded out" over the subsequent years. This pattern of results is consistent with studies of early childhood education programs, which had initial impacts that faded out and then reemerged in adulthood (Yoshikawa et al. 2013). Carrell, Hoekstra, and Kuka (2018) found weak evidence of initial test score impacts in elementary school that faded in middle school then returned in high school.[20]

One of these studies also examined "noncognitive" factors (based on teacher reports of their students' effort, initiative, class engagement, and how much they value school) and found persistent effects on those measures, suggesting that these factors provided a better medium-term forecast of impacts on adult earnings than test scores (Chetty et al. 2011).[21]

Interventions specifically targeted at children's "noncognitive" factors that have been studied through early adulthood are rarer. A notable example is Algan and coauthors' (2022) study of a childhood social skills and self-control intervention that was delivered to boys in low-income neighborhoods in Montreal in the 1980s. The program increased both self-control and prosocial skills but not other noncognitive skills (e.g., altruism, friendliness, or self-esteem). The program also did not have an initial impact on grades or school performance. But boys who received the intervention did see improved educational outcomes as adolescents and income as adults.

Drawing a broader generalization than is possible based on the five studies we reviewed would require gathering many additional data points on short- and long-term impacts, ideally based on studies that are as similar in terms of population and measures as possible.

One strategy to producing such data points is to measure the impacts of individual schools using what economists call "value-added" methods.[22] The basic idea is to measure how much each school increases (or decreases) the average outcomes of its students (e.g., test scores or adult earnings), controlling for school and student characteristics (e.g., demographics and prior test scores). This has the advantage of producing many data points on short- and long-term impacts (i.e., from many schools) in a single study, rather than needing to run a separate study to produce one data point (as in figure 2).

The only study of school-level impacts on both short-term outcomes and any dimension of economic mobility that we are aware of is Dobbie and Fryer's (2020) study of charter schools in Texas. The authors find that charter schools that increase test scores also increase earnings, but only to a point. Above-average schools (in terms of effects on test scores) do not seem to increase earnings relative to average schools, but below-average schools have a clear negative impact on earnings.[23]

This is a single study of charter schools in a single state but illustrates how studies of school-level impacts can be used to test which short-term impacts—on both test scores and any other measures, including "noncognitive" factors that can be measured at the school level—provide the best forecasts of long-run impacts.[24] These methods could also be used to better understand contextual factors operating at the school level and how they intersect with individual measures of learning and "noncognitive" factors.

In summary, we know much less about which PK–12 skills and competencies causally drive upward mobility than which are correlated with it. In a handful of studies, initial impacts on test scores appear to offer a reasonable forecast of impacts on adult earnings. And there is promising evidence that interventions that move “noncognitive” factors can have significant long-term effects and that these factors may be more useful medium-term outcomes to track than test scores.[25]

These tentative conclusions rest on a few causal studies that do not really consider contextual factors. Expanding our knowledge about which PK–12 factors causally drive mobility requires significantly expanding the number of data points connecting short- and long-term impacts. In our view, using correlational analysis to identify a clearer set of potential drivers of mobility that both predict mobility and are influenced by schools is a promising strategy for narrowing the factors that should be prioritized for causal study.

TABLE 2

Short-Term Impacts of Interventions Can Predict Long-Term Economic Impacts

Intervention	Publication	Short-term impact	Impact on wages
Childhood social skills and self-control training	Algan et al. (2022)[a]	Increased self-control and prosocial skills; did not immediately affect IQ, grades, or school performance	Increased annual income by 20 percent from ages 20–39
Exposure to disruptive peers	Carrell, Hoekstra, and Kuka (2018)[b]	Exposure to one additional disruptive peer throughout elementary school reduces test scores in grades 3–5 by 0.014 standard deviations (not statistically significant); effect is smaller in grades 6–8 and slightly larger (and significant) in grades 9–10	Exposure to one additional disruptive peer throughout elementary school reduces earnings at ages 24–28 by 3 percent
Teacher quality	Chetty, Friedman, and Rockoff (2014)[c]	Higher-quality teachers increase test scores (by 0.13 standard deviations), but impacts fade over time	A 1 standard deviation increase in teacher quality in a single grade raises annual earnings at age 25 by 1.3 percent
Classroom quality	Chetty et al. (2011)[d]	Higher-quality classrooms increase test scores (by 0.17 standard deviations); impacts fade but persist on noncognitive measures	A 1 standard deviation increase in class quality (as measured by peer scores) increases earnings at age 27 by 2.9 percent
School-level risk of receiving a low accountability rating	Deming et al. (2016)[e]	Pressure to avoid a low-performing accountability rating increased 10th-grade math scores (by 0.05 standard deviations)	Pressure to avoid a low-performing accountability rating increased earnings at age 25 by about 1 percent

[a] Yann Algan, Elizabeth Beasley, Sylvana Côté, Jungwee Park, Richard E. Tremblay, and Frank Vitaro, "The Impact of Childhood Social Skills and Self-Control Training on Economic and Noneconomic Outcomes: Evidence from a Randomized Experiment Using Administrative Data," *American Economic Review* 112, no. 8 (2022): 2553–79, https://doi.org/10.1257/aer.20200224.

[b] Scott E. Carrell, Mark Hoekstra, and Elira Kuka, "The Long-Run Effects of Disruptive Peers," *American Economic Review* 108, no. 11 (2018): 3377–415, https://doi.org/10.1257/aer.20160763.

[c] Raj Chetty, John N. Friedman, and Jonah E. Rockoff, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review* 104, no. 9 (2014): 2633–79, https://doi.org/10.1257/aer.104.9.2633.

[d] Raj Chetty, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan, "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star," *Quarterly Journal of Economics* 126, no. 4 (2011): 1593–660, https://doi.org/10.1093/qje/qjr041.

[e] David J. Deming, Sarah Cohodes, Jennifer Jennings, and Christopher Jencks, "School Accountability, Postsecondary Attainment, and Earnings," *Review of Economics and Statistics* 98, no. 5 (2016): 848–62, https://doi.org/10.1162/REST_a_00598.

The Path Forward

Empowering PK–12 educators and policymakers with a priority set of measures they can use to target student-, school-, and system-level practices and interventions and support accountability will require radically accelerating efforts to develop, identify, and validate such PK–12 measures. Student-level measures need to be rooted in a firm understanding of how they are shaped by broader factors both in and beyond schools, and there is also a need for school- and system-level measures that reflect how these structural factors directly affect mobility.

Aspects of this effort will be difficult, be time consuming, and require trial and error:

- **New student-level measures.** There are PK–12 skills and competencies that are conceptually appealing as potential drivers of upward mobility but for which widely used measures do not exist. For example, career preparation skills such as financial literacy, digital skills, and job search skills are intuitively linked to labor market success but are rarely measured. Researchers could build upon research such as that by Kreisman and Stange (2020) showing that upper-level career and technical education (CTE) courses in high school lead to higher wages and dig into the fact that many existing CTE credentials are highly correlated with math and reading scores (and potentially not measuring career preparation).[26] And there are others, including many "noncognitive" factors, for which measures do exist but higher-quality ones are needed. Developing new measures takes trial and error, and once developed, one has to wait a long time to connect the measures to upward mobility.[27]
- **Measures and analysis of broader factors.** We also need measures of the kinds of contextual factors, at the school level and beyond, that affect how students learn and how their skills translate into later success. For example, social capital is a joint product of family and broader factors, reflecting both who your parents know, who your classmates are, and the degree of connectedness across families in the same schools and neighborhoods. The degree of connectedness between individuals of low or high socioeconomic status is an important determinant of economic mobility at the county level (Chetty et al. 2022a), and there is growing interest in collecting measures of social capital in PK–12 schools (Charania and Freeland Fisher 2020). Social capital is just one example in an expansive category of structural factors that affect how much students learn at school and how that translates into long-term success, with other examples ranging from access to stable housing to school funding equity to labor market discrimination. An economic mobility agenda for PK–12 education requires identifying and measuring these factors and how they blunt or boost what students can achieve in and beyond school.
- **Upward mobility beyond income.** We know that upward mobility is about more than earning a decent income, but wages tend to cost less to measure (in large part because of the availability of administrative data) than dignity and autonomy (Acs et al. 2018). One path forward is to gather data on both economic and noneconomic dimensions of mobility to understand which noneconomic measures add the most value (i.e., are least correlated with the economic

measures) and thus should be prioritized for collection in future research. And there may be nonwage elements of job quality that could be measured using administrative records (e.g., based on information about employers, occupations, or industries).

At the same time, this review of the evidence suggests the existence of significant "low-hanging fruit" that could accelerate progress using data that already exist:

- **Harness state data systems.** Most states have longitudinal data systems that follow students' paths from PK–12 through postsecondary education and the workforce (Data Quality Campaign 2018). These linked data could be used to perform correlational analyses of earnings and any PK–12 measures, including test scores, that were tracked far enough in the past to be linked to the earnings data. Within the test score category, researchers should prioritize building on what we know about summative math and reading scores, such as by studying domains of these subjects or other subjects. Other possibilities include scores on formative assessments, performance in CTE courses, and measures of social-emotional learning. Researchers should also prioritize understanding how relationships vary by student groups (including socioeconomic status, race or ethnicity, and gender) and by structural factors that vary across schools or school systems (which may be most feasible in larger and more diverse states).
- **Learn from school-level impacts.** There is a robust literature identifying the impacts of individual schools on a range of skills and competencies.[28] Combined with linked data systems, this methodological machinery could support the identification of upward mobility drivers by linking school impacts on near-term measures such as test scores and "noncognitive" factors to the impacts the same schools have on earnings. This approach is also ripe for understanding broader factors that vary at the school level, including those that can be measured (e.g., funding levels and disciplinary policies) and those that might be identified based on mobility data (e.g., what are schools with higher mobility rates after controlling for test scores doing different from schools with lower mobility rates?).
- **Apply an upward mobility lens.** Nearly all studies of earnings impacts use a traditional labor economics approach of analyzing earnings as a continuous measure for all students in a dataset. Researchers can test whether applying an upward mobility lens instead would produce different results, including by restricting samples to children who grew up in low-income families and testing different income thresholds for achieving upward mobility. And, when data allow, whether nonwage dimensions of mobility, such as job quality, dignity, and autonomy, paint a different picture than wages alone.

- **Organize short- and long-run impact evidence.** As researchers continue to produce long-run follow-up studies of earlier interventions, more evidence that connects short- and long-run impacts will become available. An important effort to organize this information is Opportunity Insights' Library of Early Indicators.[29]
- **Deepen examination and discussion of heterogeneity of effects.** Studies regularly control for race, gender, and other sociodemographic variables. Occasionally, they examine how outcomes differ by these or individual characteristics, though discussions of findings tend to be limited. The analytical methods and cross-system datasets that are needed to robustly study multidimensional, longitudinal structural oppression are still emerging. But existing frameworks for conducting research through a structural lens can guide current studies (Balu et al. 2023). Similarly, empirical researchers can benefit from established bodies of conceptual literature on the effects of structural and systemic oppression and opportunity on outcomes (Dixson and Anderson 2018; Ladson-Billings and Tate 1995; Levinson and Cohen 2023).

Identifying drivers of upward mobility in PK–12 schools will benefit from an interdisciplinary approach that brings together, for example, psychologists who study the social interactions that support "noncognitive" factors and the social factors that affect whether these factors translate into economic mobility, economists who think about the structure of labor markets, psychometricians who develop standardized assessments of academic skills, and sociologists who probe the structural forces that shape how schools operate and how students learn.

Taking a conceptually appealing potential mobility driver to a fully validated measure is a lengthy endeavor, from developing a new measure, to testing its validity for specified purposes, to assessing its relationship to upward mobility, to finally confirming that it causally drives mobility. This process is likely to have bumps along the way, as not all measures will pass muster at every stage. And some will appear promising but then run into the realities of real-world data collection and use, with high-stakes uses often degrading the usefulness of an indicator.

But there is much that educators and policymakers can learn along the way in partnership with researchers. For example, a research project that developed and tested new measures of student motivation could inform educators in a school district about differences in measured motivation levels across different groups of students, how motivation is affected by teacher expectations (and how this intersects with having a same-race teacher), and how this shapes how motivation translates into academic achievement for different students (Silverman et al. 2023).

Seeking to understand which PK–12 skills and competencies drive upward mobility—and how to best measure them—raises fundamental questions about what makes for a high-quality education. Answering more of these questions within a framework oriented toward upward mobility will have the dual benefit of supporting educational improvement today, even as connecting those improvements to lifelong success is a lengthier endeavor.

Notes

[1] Duncan, Gootman, and Nalamda (2023), citing Chetty and coauthors (2020), report that children who grew up in the poorest 20 percent of families have a 34 percent chance of staying there as adults. This problem is not equally felt, with 37 percent of Black Americans and nearly half of Native Americans experiencing intergenerational poverty, compared with 29 percent of white people. See also Acs, Elliott, and Kalish (2016).

[2] There is also evidence that schools are limited in their ability to bolster upward mobility by factors beyond their control. Rothstein (2019) shows that a small portion of an area's rates of economic mobility is explained by test scores at the end of high school. He finds significant variation in the future economic outcomes of adolescents with similar achievement levels, perhaps because of features of local labor markets, such as discrimination or unions.

[3] For example, Chetty and coauthors (2011) and Chetty, Friedman, and Rockoff (2014) examine longer-term outcomes, including college enrollment. We also do not review approaches, such as the Urban Institute's Social Genome Model, that use matched panel datasets to model outcomes over the life course (Acs et al. 2022).

[4] We are grateful to Margery Austin Turner for suggesting this typology.

[5] For more in-depth discussions of structural factors that affect educational outcomes and economic mobility, see Rothstein (2017) and "Evidence Resource Library," Urban Institute, accessed February 28, 2024, https://upward-mobility.urban.org/evidence-resource-library?text=&domains=74&drivers=All.

[6] We focus on studies from the US, but a notable study of UK data is Watts (2020), which finds that a 1 standard deviation increase in math scores is associated with a 5 to 7 percent increase in average monthly earnings from age 33 to age 50. For reading scores, the association is 5 to 8 percent.

[7] See Lin, Litter, and Ruhm (2023, figure 3); numbers are sourced from the replication package, available at https://www.dropbox.com/sh/xff0m2polmqj7zh/AADgm3bYupjePWHuvW9XhtQIa?dl=0.

[8] Notable sample limitations that might affect how their results compare with those from other studies include dropping from the sample individuals with earnings below $1,000, those who did not graduate from high school, and anyone who did not identify as Black, Hispanic, or white.

[9] These estimated relationships control only for individual race or ethnicity (Black, Hispanic, or white).

[10] In practice, the correlations between reading scores and earnings were positive but not statistically significant in models that also included math scores. Murnane and coauthors (2000) report, "The simple correlation coefficients between the math score and subsequent earnings and between the reading score and subsequent earnings are as follows: 0.25 and 0.19 for NLS72 males; 0.23 and 0.18 for NLS72 females; 0.20 and 0.13 for HS&B males; and 0.26 and 0.19 for HS&B females."

[11] This study does not distinguish between how much of the relationship is accounted for by prior-year test scores (which are included at the student, classroom, and school levels) compared with the other student-, classroom-, and school-level controls.

[12] Former Institute of Education Sciences director John Easton (2013, 8) said of "noncognitive" factors, "Everybody hates this term but everyone knows roughly what you mean when you use it and no one has a much better alternative."

[13] Segal (2013) also finds that, consistent with Papageorge, Ronda, and Zheng (2022), teacher reports of disruptive behavior by students was associated with higher earnings. But the author notes that disruptive behavior is associated with lower earnings when the other types of misbehavior are excluded from the analysis.

[14] Libby Stanford and Caitlyn Meisner, "Social-Emotional Learning Persists Despite Political Backlash," *Education Week*, July 27, 2023, https://www.edweek.org/leadership/social-emotional-learning-persists-despite-political-backlash/2023/07.

[15] Another example is Judge and Hurst's (2007) study of "positive core self-evaluations" (a mix of self-esteem, self-efficacy, emotional stability, and locus of control) using NLSY79 data, where they note that "among individuals without early advantages, positive CSEs do little to enhance future earnings.... In that case, interventions that attempt to alter CSEs among disadvantaged youth without changing their circumstances, or vice versa, may not have the desired impact on their long-term material success."

[16] See D'Mello, Dieterle, and Duckworth (2017) for an approach to measuring engagement in digital learning environments.

[17] Athey and coauthors (2019) provide a useful framework for consolidating multiple short-run indicators into a "surrogate index" that forecasts a specified long-term outcome.

[18] In some cases, we can piece together short- and long-run impacts from separate studies, but this typically reduces comparability (e.g., because of differences in methodology).

[19] We included studies with plausibly causal estimates of impacts on both PK–12 measures and labor market outcomes based on datasets comprising a substantial number of students (we did not use a precise cutoff, but, for example, we did not include the small-scale Abecedarian and Perry Preschool studies).

[20] Carrell, Hoekstra, and Kuka (2018) found that test score effects, which were initially observed in grades 3–5 but were not statistically significant, were smaller in grades 6–8, and then returned to their approximately prior size in grades 9–10 (and were then statistically significant). But given the precision of the estimates, the authors could not statistically distinguish between the test score effects across grade levels.

[21] There is also evidence that expanding the definition of teacher quality to include non–test outcomes, such as absences and suspensions, more than doubles the strength of the relationship between the short-term impact of teachers and long-term outcomes such as high school completion (Jackson 2018).

[22] Yet another approach that may be more feasible in some circumstances but is less causally persuasive is to compare changes in PK–12 measures and earnings at some level of geographic aggregation. For example, Doty and coauthors (2022) show that states that increased their eighth-grade math scores on the National Assessment of Educational Progress saw larger increases in average earnings over the same period.

[23] Looking separately at impacts on math and reading scores, the impact on reading scores appears to be more predictive of the impact on earnings throughout the distribution of test score impacts.

[24] Researchers using this strategy would have to consider evidence indicating that school value-added estimates that are not based on lotteries may be biased and how much this matters for forecasting economic outcomes (Angrist et al. 2017).

[25] A recent meta-analysis that looked only at short- and medium-term effects, though, found that cognitive and "noncognitive" skills demonstrated similar degrees of fade-out (Hart et al. 2023).

[26] Much CTE research relies on and acknowledges the challenges of using the number of CTE courses and units or CTE credentials (a range of national vendor tests and industry-recognized credentials usually coded as pass-fail) to measure the quality of CTE. Kreisman, Figge, and Villero (2021) begin to interrogate the question of what skills CTE is teaching by examining correlations between CTE assessment scores and math and English language arts scores.

[27] In some cases, early evidence might be produced by administering the measure to young adults and collecting data on their contemporaneous earnings (as has been done extensively in the personality psychology literature).

[28] We do not review much of this research in this report, given our focus on studies that include economic outcomes, but examples of studies in the school value-added literature include Deming (2014), Angrist et al. (2017, 2024), Beuermann et al. (2023), and Bacher-Hicks, Billings, and Deming (2019).

[29] "Library of Early Indicators," Opportunity Insights, accessed February 28, 2024, https://opportunityinsights.org/data/library-of-early-indicators/.

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