in press, *Psychological Science*

Cognitive Skills, Student Achievement Tests, and Schools

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Acknowledgements:

This research was funded by the Bill & Melinda Gates Foundation (to J.D.E and C.F.O Gabrieli) and the National Institute of Health (NRSA to A.S.F). We thank J. Salvatore, B. Khalil Peabody, and A. Mackey for assistance in this research.

Abstract

Cognitive skills predict academic performance, so schools that improve academic performance might also improve cognitive skills. To investigate the impact schools have on both academic performance and cognitive skills, we related standardized achievement test scores to measures of cognitive skills in a large sample (N=1,367) of 8th-grade students attending traditional, exam, and charter public schools. Test scores and gains in test scores over time correlated with measures of cognitive skills. Despite wide variation in test scores across schools, differences in cognitive skills across schools were negligible after controlling for 4th-grade test scores. Random offers of enrollment to over-subscribed charter schools resulted in positive impacts of such school attendance on math achievement, but had no impact on cognitive skills. These findings suggest that schools that improve standardized achievement tests do so primarily through channels other than cognitive skills.

A fundamental goal of education is to equip students with the knowledge and skills necessary to think critically, solve complex problems, and succeed in the 21st century society and economy. Measurement of such knowledge and skills is essential to tracking students' development and assessing the effectiveness of educational policies and practices. Education and psychological science have examined these issues in nearly complete separation. Education researchers have used many measures of learning, but recent research has drawn primarily on standardized achievement tests designed to assess students' mastery of state-defined content standards in core academic subjects (Borman, Hewes, Overman, & Brown, 2003; Hanushek & Rivkin, 2010). Psychological science has used measures of several cognitive concepts to assess variation in domain-independent mental skills, including processing speed (how efficiently information can be processed (Kail & Salthouse, 1994)), working memory capacity (how much information can be simultaneously processed and maintained in mind (Cowan, 2005; Gathercole, Pickering, Knight, & Stegmann, 2004)), and fluid reasoning (how well novel problem can be solved; also termed fluid *g* (Engle, Tuholski, Laughlin, & Conway, 1999)). The present study integrated these two approaches to measuring knowledge and skills by asking how the enhancement of academic performance by schools relates to the types of cognitive skills studied in psychological science.

Studies of cognitive development have focused on processing speed (PS), working memory (WM) capacity, and fluid reasoning (FR) as three inter-related cognitive abilities that develop markedly from childhood through adulthood and that predict individual differences in performance on numerous measures (Cowan et al., 2005). Studies from late childhood through young adulthood indicate that gains in PS support gains in WM capacity that, in turn, support FR (Coyle, Pillow, Snyder, & Kochunov, 2011; Fry & Hale, 1996; Kail, 2007).

These maturing mental abilities are thought to broadly underpin learning and cognitive skills. Variation in these measures predicts performance on a wide range of tasks among adults, including comprehension (Daneman & Carpenter, 1980), following directions, vocabulary learning, problem solving, and note-taking (Engle, Kane, & Tuholski, 1999). Critically, these cognitive abilities are associated with academic performance. Executive function measured in preschool predicts performance on math and literacy in kindergarten (Blair & Razza, 2007), and parental reports of attention span-persistence in 4-year-olds predicts college completion at age 25 (McClelland, Acock, Piccinin, Rhea, & Stallings, 2013). Likewise, WM skill correlates with math and reading ability among 5- and 6-year olds (Alloway & Alloway, 2010) and among 11- and 12-year olds (St Clair-Thompson & Gathercole, 2006), and predicts mathematics and science achievement among adolescents (Gathercole et al., 2004). Thus, cognitive skills appear to promote or constrain learning in school.

Although cognitive skills are seldom taught explicitly in schools, research indicates that schooling can promote cognitive skills in children. Using age cut-offs that determine the age young children are enrolled in schools, studies have shown that attending (versus not attending) school for a year (Burrage et al., 2008) or attending school for more years (McCrea, Mueller, & Parrila, 1999) was associated with better performance on tests of working memory and executive functions. Reviews of the empirical literature examining the relationship between schooling attainment and IQ reveal a consistent positive relationship between time spent in school and measures of intelligence (Ceci, 1991; Ceci & Williams, 1997). These observational studies suggest that school attendance can improve cognitive skills beyond what is taught directly.

What is unknown, and crucial for informing educational policy, is whether general educational practices that increase academic performance also have a positive impact on basic cognitive skills. Schools traditionally focus on teaching knowledge and skills in content areas, such as mathematics and language arts. Use of such knowledge can be referred to as *crystallized* intelligence (Cattell, 1967). In contrast, *fluid* intelligence refers to the ability to solve novel problems independent of acquired knowledge; the cognitive measures in the present study are indices of fluid intelligence. Do schools where students are experiencing high levels of academic success in crystallized intelligence achieve this success by promoting the growth of fluid cognitive abilities? The strong relation between cognitive ability and academic performance suggests that schools that are particularly effective in improving academic performance may also improve domain-independent cognitive skills..

To shed light on this issue, we examined the relations between scores on standardized tests in mathematics (Math) and English language arts (ELA) on the Massachusetts Comprehensive Assessment System (MCAS) and measures of cognitive skills among 1,367 8th graders attending traditional district, (test-in) exam, and charter public schools in a large urban school district. First, we asked whether there was an association between 8th-grade MCAS scores, gains in MCAS scores between 4th and 8th grade, and cognitive skills. Second, we compared the share of the overall variance in MCAS scores and cognitive skills explained by the school attended in 8th grade. Finally, we asked whether attending one of five over-subscribed charter schools that select students randomly by lottery and that generate consistent achievement gains on the MCAS (Abdulkadiroglu, Angrist, Dynarski, Kane, & Pathak, 2009; Angrist, Cohodes, Dynarski, Pathak, & Walters, 2013) also led to similar gains in cognitive skills.

Method

Participants

From among 1,852 8th grade participants, results are reported for 1,367 students for whom there were test score data from both 4th and 8th grades (47% male, 77% free-lunch eligible, 41% African-American, 36% Hispanic, 12% White (non-Hispanic); Supplemental Table S1).

Apparatus and Stimuli

Participants were tested as groups in classrooms and recorded responses in booklets. Stimuli were presented on a projector. Students completed the tasks, all adapted for group classroom administration, in the order presented below with a proctor, an additional experimenter, and a teacher present.

<u>Processing Speed (PS)</u> For the Coding and Symbols tests from the Wechsler Intelligence Scale for Children IV (WISC-IV), students were asked to 1) translate digits into symbols by referring to a corresponding digit-symbol key (nine novel symbols corresponded to digits 1-9), and 2) indicate if any of two symbols on the left side of a page matched any of five symbols on the right side of a page. Students had two minutes to complete each task.

<u>Working Memory (WM)</u> For the count-span task (Case, Kurland, & Goldberg, 1982; Cowan et al., 2005), students viewed an array with blue circles, blue triangles, and

red circles, and were instructed to count only the blue circles (targets) within 4.5 seconds. After one or more arrays were presented, students were presented with a prompt to write separately the number of targets presented in each display. Load ranged from 1-6 consecutive arrays and increased by one after three instances of a particular load.

Fluid Reasoning (FR) For the Test of Nonverbal Intelligence (TONI-4, version A), students chose which of 6 pictures completed the missing piece of a puzzle. Choosing the correct response required the integration of progressively more difficult information (such as shape, pattern, and orientation). Students completed as many of 40 puzzles possible in 10 minutes.

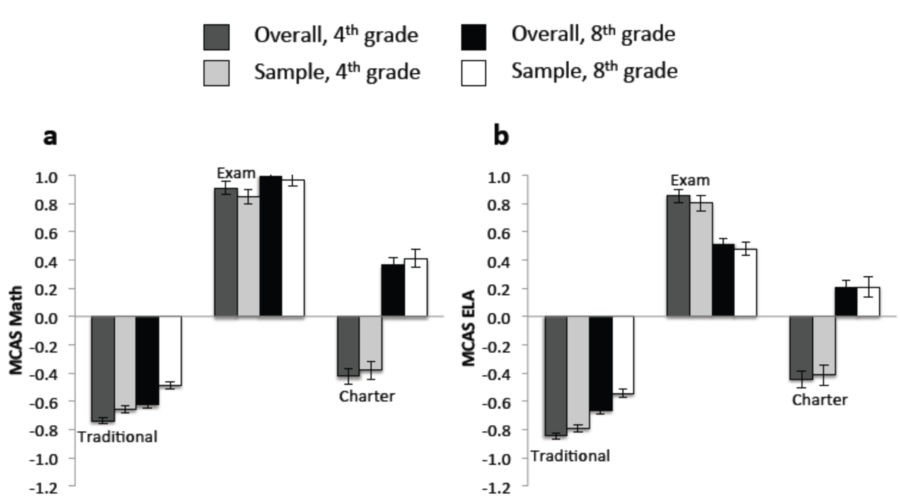
Procedure

Composite Cognitive Measure Because the three measures of cognitive skills were moderately correlated (r ranged from 0.23 to 0.32, $p<.001$), we combined them into a composite reflecting general cognitive ability with greater breadth and reduced measurement error. We standardized each measure to have mean zero and unit variance and averaged these standardized scores.

MCAS scores and charter lottery status We obtained school enrollment and demographic information and MCAS Math and ELA scores from databases maintained by the Massachusetts Department of Elementary and Secondary Education. MCAS scores were standardized to have mean zero and unit variance by grade, subject, and year across all tested students in Massachusetts. Data from the admissions lotteries used to admit participating students were acquired directly from the charter schools. Lottery records were matched to state administrative data using names, year, and grade of application, yielding a total of 702 verified lottery participants (won (n=481) or lost (n=221); Supplemental Figure S1).

Results

<u>*Representativeness of Sample*</u> To examine how representative participating students were of public school students in the school district, we compared the 4th and 8th grade MCAS scores for students in our sample to all students in the school district (Supplementary Figure S1), and made the same comparisons separately for traditional, exam, and charter schools (Figure 1). The study sample was generally representative of the student population in the district public schools, although participating students in traditional schools scored slightly higher than their non-participating peers on the 8th-grade Math and ELA MCAS. Exam school students scored highest, reflecting their admission to those schools based on test performance. Notably, students admitted to charter schools via random lotteries moved from below the statewide average to well above average between 4th and 8th grade.



Relations of MCAS Scores to Cognitive Measures We examined the relations between MCAS scores and the PS, WM, FR, and composite measures. Bivariate Pearson correlations revealed significant and positive relations between Math scores and cognitive measures (PS (r=.46, p<.001); WM (r=.27, p<.001); FR (r=.53, p<.001); composite (r=.57, p<.001)) and also between ELA scores and cognitive measures (PS: r=.38, p<.001; WM: r=.18, p<.001; FR: r=.36, p<.001; composite r=.40, p<.001).

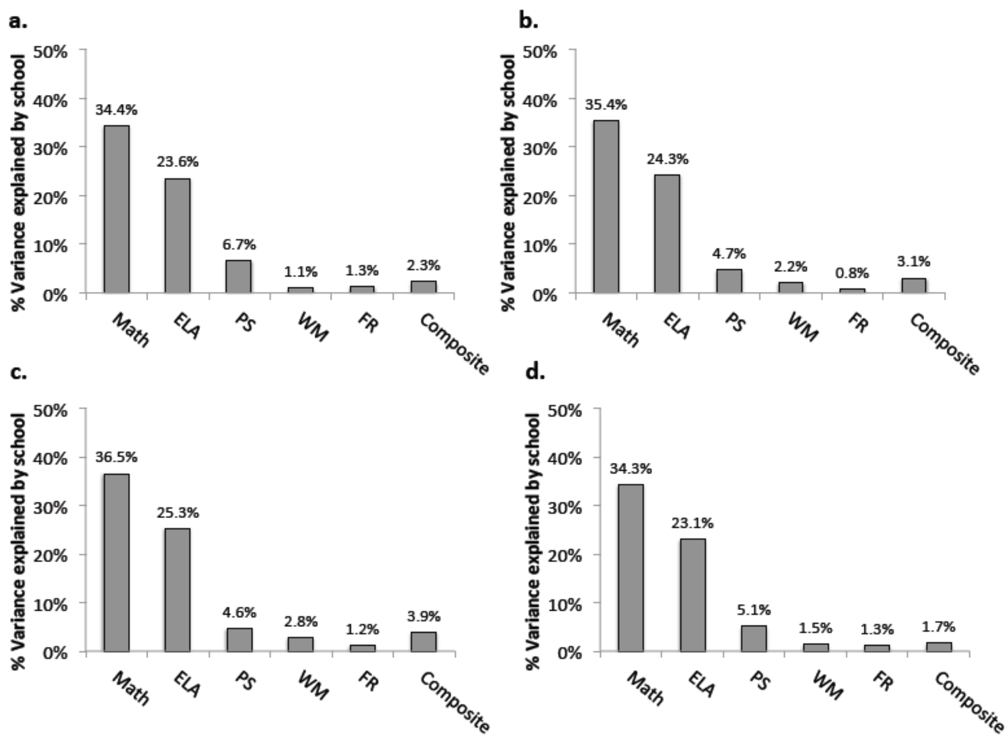
Relations of Gains in MCAS scores to Cognitive Measures To explore the relations between cognitive measures and MCAS scores collected in 4th and 8th grades (independent of one another), we conducted a path analysis (Figure S3). For both Math and ELA, we found positive and statistically significant relations between both 4th- and 8th-grade test scores and each cognitive measure. Measures of cognitive ability could be correlated with 8th-grade achievement independent of 4th-grade achievement because assessments administered contemporaneously in 8th grade are more related to one another than to an assessment administered in 4th grade, or because the 8th-grade tests assessed more cognitively complex topics than the 4th-grade tests, or because of the influence of other factors that affected both types of outcomes between 4th and 8th grade.

To provide additional evidence that improvement on MCAS tests was related to cognitive performance, we calculated achievement gains for each student as the difference between students' 8th-grade test scores and their predicted scores based on a multivariate model with cubic functions of 4th-grade student achievement in both Math and ELA. These gains correlated positively with cognitive measures, with stronger correlations in Math (PS: r=.29, p<.001; WM: r=.12, p=.001; FR: r=.32, p<.001; composite r=.32, p<.001) than in ELA (PS: r=.21, p<.001; WM: r=.04, p=.2; FR: r=.19,

$p<.001$; composite $r=.18$, $p<.001$), suggesting that overall academic improvement, which here includes any gains attributable to the school attended and gains attributable to other individual and contextual factors, was related to cognitive ability.

Relations of Schools to MCAS Scores and Cognitive Measures. To probe the impact of schools on each of these measures, we first asked how much of the observed variance in each of the 8th grade MCAS test scores and each of the cognitive measures can be explained by which school a student attended. Specifically, we decomposed the total variation in MCAS and cognitive scores into variation in the average scores (separately for each test (Math and ELA) and cognitive measures (PS, WM, FR and Composite)) between the 32 schools in our sample and variation in the scores of individual students within each of these schools. These analyses of variance (ANOVAs) controlled for 4th-grade MCAS scores and demographics (gender, race, age, free and reduced-priced lunch status, limited-English-proficient, and special-education status). Schools explained between 24% (ELA) and 34% (Math) of variation in 8th-grade MCAS scores in our sample (conditional on 4th-grade achievement), but less than 7% of variation in PS, less than 2% for WM and FR, and less than 3% of the composite cognitive construct (Figure 2a).

This pattern of large variation in achievement but minimal variation in cognitive measures across schools was also observed when performing these same analyses with additional controls for either 8th-grade MCAS scores (in the analyses of cognitive measures) or cognitive performance measured in 8th grade (in the analyses of 8th-grade MCAS scores). Specifically, the same pattern was observed 1) when controlling for 8th-grade MCAS in assessing how much variation schools explain in cognitive measures and controlling for cognitive performance (composite cognitive measure) in assessing how much variation schools explain in achievement (Math and ELA MCAS) (Figure 2b); 2) when removing the controls for 4th-grade MCAS performance in the original analysis and controlling for 8th-grade MCAS in assessing how much variation schools explain in cognitive measures, and controlling for cognitive performance (composite cognitive measure) in assessing how much variation schools explain in achievement (Math and ELA) (Figure 2c); and 3) when excluding exam schools, which selectively admit students based on test scores (Figure 2d). Even when controlling for cognitive skill and achievement in various ways, schools consistently accounted for a large amount of variation in achievement test scores, but minimal variation in cognitive measures.



Impact of Charter School Attendance on MCAS Scores and Cognitive Measures

A second, quasi-experimental analysis directly examined this relationship by asking whether five over-subscribed charter schools that improved MCAS scores also improved cognitive skills. Following a study of over-subscribed charter schools (Abdulkadiroglu, Angrist, Dynarski, Kane, & Pathak, 2011), we used the random offer of enrollment to these schools to estimate the effect of charter attendance on MCAS scores and cognitive skills. Outcomes were compared between 8th graders who applied and randomly won (n = 143) or lost (n = 57) the lottery for admission to these charter schools, with adjustments for the fact that not all lottery winners entered and remained enrolled in a charter school. Following previous work (Abdulkadiroglu et al., 2011), we fit the following model:

$$\text{(I. a)} \quad Y_{is} = \alpha A_{i,t-4} + \beta YEARS_{is} + \lambda X_i + \sum_j \delta_j d_{ij} + \epsilon_{is}$$

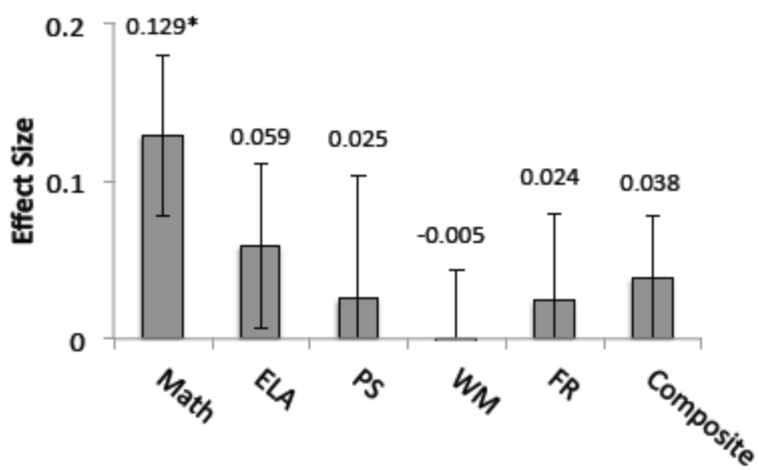
The outcome of interest (Y_{is}) represents a given test score or measure of cognitive skill for student *i* in school *s*. We included as controls lagged 4th-grade scores in Math and ELA ($A_{i,t-4}$) and a vector of student demographic characteristics (X_i,) consisting of variables for gender, race, age, free and reduced-priced lunch status, limited English proficiency, and special education status. The set of indicator variables d_{ij} controls for lottery "risk sets," or the unique combination of lotteries to which each student applied, indexed by j. Parameter β represents the quantity of interest, the effect of attending a year at one of the five over-subscribed charter schools.

To arrive at a causal estimate of β, we isolated exogenous variation in $YEARS_i$, our measure of the number of years a student attended a charter school. We did this by employing the random (within lottery "risk sets") offer of enrollment as an instrument for charter attendance with the following first-stage model:

$$\text{(I. b)} \qquad YEARS_{is} = \gamma_1 OFFER_i + \theta A_{i,t-4} + \tau X_i + \sum_j \rho_j d_{ij} + \xi_{is}$$

The indicator variable for whether a student was randomly offered enrollment to any of the five charter schools, $OFFER_i$, provides a valid instrument for $YEARS_{is}$. We also included the full set of covariates included in the second-stage model above.

Each additional year of charter attendance was estimated to increase 8^{th}-grade Math scores by 0.129 standard deviations (*p*=0.018), with no significant effects for ELA scores. Despite the increase in MCAS Math scores, we observed virtually no effect of oversubscribed charter school attendance on cognitive skills, considered individually or as a composite (Figure 3)[1].



Discussion

This study is the first to relate scores on statewide standardized achievement tests to measures of cognitive skills in a large and representative sample of students in a city that includes traditional district, exam, and charter public schools. We found substantial positive correlations between cognitive skills and achievement test scores, especially in math. These correlations are consistent with prior studies relating working memory to academic performance (grades) in UK schools (Alloway & Alloway, 2010; Alloway & Passolunghi, 2011; Gathercole et al., 2004; St Clair-Thompson & Gathercole, 2006). We also extend prior research by documenting a relationship between cognitive skills and growth of achievement test scores from 4^{th} to 8^{th} grade.

However, two convergent findings suggested that the school a student attended in the district we studied played little role in the growth of cognitive skills. First, which school students attended explained substantial variance in students' achievement scores, but not in measures of their cognitive skills. Second, the sample included winners and losers of lotteries for over-subscribed charter schools. In Massachusetts, students who won admission to and attended an urban charter schools through these lotteries achieved substantial test score gains above those students that lost the lotteries (Abdulkadiroglu et al., 2011). We replicated that finding for Math (but not ELA) scores (school impacts on Math scores are frequently larger than on ELA scores). Attending a charter school as a result of winning a seat through an admission lottery, however, did not significantly impact students' cognitive skills. These findings suggest that school practices that influence standardized achievement tests have limited effects on the development of cognitive skills associated with processing speed, working memory, or fluid reasoning.

The present study has multiple caveats. First, our sample was limited to 1,367 students in 32 schools of the 3,151 students in 49 schools from one district who took the MCAS in both 4^{th} and 8^{th} grade. One source of potential bias was parental consent for student participation, a bias that may favor students from more supportive households. The sample of students from traditional district schools scored higher on the statewide tests than did the overall population in these schools, suggesting that the sample from these schools was biased towards higher-achieving students. Second, although analysis of the effects of attending a charter school has the rare benefit of being able to exploit the random offer of enrollment to make quasi-experimental comparisons, there were especially few lottery losers in this sample.

Although the lottery-based admission of students to oversubscribed charter schools creates a natural experiment among lottery applicants, the present study is neither an evaluation of charter schools in general, nor a direct comparison of charter, traditional, and exam schools. Gains in student achievement varied across all three school types, with some traditional schools having higher average gains than some charter schools (Figure S4).

The finding that variation in schooling influences crystallized but not fluid intelligence is consistent with a population study of over 100,000 males in Sweden (Carlsson, Dahl, & Rooth, 2012). Crystallized and fluid intelligence are typically correlated, as were the MCAS and cognitive skills measures in the present study, and it appears that effective schools, including the over-subscribed charter schools and some of the traditional district schools in the present study, may be decoupling these two kinds of intelligence.

These findings raise the question of what kinds of abilities are indexed by high-stakes statewide standardized tests that are widely used as a measure of educational effectiveness. Several lines of evidence indicate that students' scores on standardized achievement tests predict important long-term educational and socioeconomic outcomes. Student achievement scores in math and reading at age 7 are associated positively with adult socioeconomic status (SES) and educational attainment at age 42 even after controlling for SES at birth and intelligence measures (Ritchie & Bates, 2013). Further, charter high schools that produce large gains on standardized tests also improve student performance on Advanced Placement tests and SATs (especially in math, as in the present study) (Angrist et al., 2013). Finally, gains in standarized test scores due to classroom quality (i.e., class size and teacher effectiveness) in primary school are also associated with positive SES outcomes in adulthood (Chetty et al., 2011). It is unknown, however, how a selective enhancement of crystallized intelligence, without the enhancement of typically correlated fluid intelligence, translates into long-term benefits for students, and whether additional enhancement of fluid intelligence would further bolster long-term educational and SES outcomes.

Although school-level educational practices that enhance standardized test scores may not increase broader, fluid cognitive abilities, there is evidence that targeted interventions—both in and out of school— may increase cognitive ability. Preschoolers enrolled in a year-long executive function training curriculum improved performance on untrained executive function tests (Diamond, Barnett, Thomas, & Munro, 2007). Children receiving an intervention emphasizing the development of cognitive and conceptual skills (among other interventions, “the Abecedarian Project”) from birth to either 5 or 8 years of age, performed better on both standardized intelligence (IQ) and academic tests (Campbell, Ramey, Pungello, Sparling, & Miller-Johnson, 2002). Teaching inductive reasoning to third and fourth grade students improved performance on untrained reasoning tests and a fluid reasoning measure (Raven's Progressive Matrices) if the intervention lasted for two years (de Koning, Hamers, Sijtsma, & Vermeer, 2002). Seventh graders in Venezuela showed gains on multiple standardized tests following an intensive year of cognitive training, although the benefits were not apparent on tests characterized as reflecting fluid, content-independent cognitive skills (Herrnstein, Nickerson, & de Sánchez, 1986). Eight-week training in after-school programs focused on either reasoning or speed training selectively enhanced performance in 7-9 year-olds (Mackey, Hill, Stone, & Bunge, 2011).

In addition to the above in-school studies, interventions performed outside of school have also shown that working memory or attention training exercises conducted over the course of several weeks can improve cognitive skills beyond those that are trained directly (Bergman Nutley et al., 2011; Klingberg, 2010; Rueda, Rothbart, McCandliss, Saccomanno, & Posner, 2005) and improve performance on tests of math and literacy (Maridaki-Kassotaki, 2002; Rajah, Sundaram, & Anandkumar, 2011; Witt, 2011). Although a broader understanding of which aspects of cognitive skill are malleable and which interventions are effective and why is still emerging, the above studies indicate that targeted interventions may boost cognitive skills in students.

In sum, the present study provides further evidence that schools influence standardized test scores that reflect crystallized knowledge. The growth of math and language skills that schools can support may be especially important for students growing up in disadvantaged environments that typically offer fewer opportunities for academic enrichment outside of school. The same schools, however, had no apparent influence on cognitive skills reflecting fluid intelligence. Given the evidence that cognitive skills were associated with not only standardized test scores but also with the growth of those scores from 4th to 8th grade, students may further benefit from school practices that enhance cognitive skills. The development of curriculum that fosters the growth of cognitive skills may further nurture the academic and long-term success of students.

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Footnote

1. Sample sizes for these analyses vary due to missing data on cognitive measures (n=200 (MCAS Math, MCAS ELA, and PS); n=188 (WM); n=185 for (FR); n=176 (Composite)).

Figure Captions

Figure 1. Mean Massachusetts Comprehensive Assessment System (MCAS) scores by school type. Scores are plotted for students overall (dark bars) and students in study sample (light bars), separately for Math (a) and English language arts (ELA) (b). MCAS scores were standardized by subject, grade, and year to have mean zero and unit variance in the population of students attending Massachusetts public schools. Error bars represent plus/minus one standard error of the mean.

Figure 2. Variance explained by schools for 8th-grade MCAS scores and cognitive measures of processing speed (PS), working memory (WM), fluid reasoning (FR), and composite cognitive measure (Composite). Percentage of school-level variance for each outcome was calculated using ANOVA with different controls: controlling for student demographics and 4th-grade MCAS scores across all measures (a), controlling for demographics and 4th-grade MCAS score for all outcomes and the composite cognitive measure for test scores (Math and ELA) and 8th-grade MCAS scores (Math and ELA) for cognitive measures (PS, WM, FR, Composite) (b), controlling for demographics for all outcomes and the composite cognitive measure for test scores (Math and ELA) and 8th-grade MCAS

score for cognitive measures (PS, WM, FR, Composite) (c), and controlling for student demographics and 4th-grade MCAS scores across all measures, but excluding students from exam schools (d).

Figure 3. Estimated impact of one year's attendance at an over-subscribed charter school. Quasi-experimental estimates (based on random offer of admission) depict the effect of each additional year of charter attendance on MCAS scores and cognitive skills. Error bars represent plus/minus one standard error of the estimated effect.