China Economic Review 55 (2019) 199–217

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Better cognition, better school performance? Evidence from primary schools in China

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ARTICLE INFO

Keywords:
Cognition
School performance
Primary school
China

JEL code:
I21
I24
J24

ABSTRACT

Although students in rural and migrant schools in China generally have not performed well, a share of each cohort has been able to thrive in school and to test into academic high school and college. To understand the origins of persistence, specifically, why some students learn more than do others, researchers have identified certain sources of the problem. Few studies, however, have paid attention to the role that low levels of cognitive development of students play in their academic performance. To address this gap, this study focuses on the role that cognition may play in terms of the academic achievement of rural students. We analyze data from more than 10,000 primary school students from private migrant schools in Beijing and Suzhou and from public rural schools in Henan and Anhui, using the Raven Standard Progressive Matrices test. Our results show high rates of developmental delay (about 33% of the students have Ravens scores that are less than one standard deviation lower than an international mean). Further, the rates of delay are large among all subgroups in the study, including rural children who attend migrant schools in cities and those who live in rural areas and attend rural public schools. The results also suggest that the cognition of students is highly correlated with their educational performance and, in fact, is by far the most important factor in their academic achievement.

1. Introduction

The literature shows that, among rural children across China, there are large gaps in learning (Zhang, Jin, Toreto, & Li, 2018). Research that uses learning data that are representative of rural children across China shows that the distribution of academic achievement is quite flat (Xu & Xie, 2015). Specifically, research has shown that there are many students who have high levels of learning when they are in primary school as well as many students in which learning levels are substantially lower (Chen & Feng, 2019). Other research finds that more than half of the primary school-aged children in rural areas of China are not ready for the next stage of their education (Zhou et al., 2015). Finally, Yang, Sicular, and Lai (2014) and Wang et al. (2018) show divergence in learning among students in rural junior high schools.

To understand these differences among students, researchers have identified a variety of factors. Notably, the education system puts rural children at a disadvantage at different points in the educational process. Some schools have certified, highly educated teachers, while others have poor quality, temporary contract teachers (Luo et al., 2012; Wang, Luo, Zhang, & Rozelle, 2017). Further,

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https://doi.org/10.1016/j.chieco.2019.04.005
Received 11 January 2019; Received in revised form 11 April 2019; Accepted 11 April 2019
Available online 17 April 2019
1043-951X/

health and nutrition problems plague some rural elementary school students in China's impoverished regions (Bai et al., 2018). The quality of boarding facilities also has been shown to have a negative impact on the learning of the large share of rural students who live at school during the week (Wang et al., 2011).

Although research has focused on these systemic factors (both inside and outside of China), scant attention has been paid in the literature in China to the lifelong importance of the development of high levels of cognition and language ability early in a child's life. In contrast, there is a large and growing literature internationally (Cortázar, 2015; Hu, 1997; Nores & Barnett, 2010). Heckman & Raut (2016), for example, show strong correlations between low levels of cognition in 2- to 3-year-olds and their later school performance and eventual attainment. In a systematic review, Nores and Barnett reviewed a total of 38 control studies and 30 intervention studies in 23 countries and found that children in a variety of countries receive sustained cognitive, behavioral, health, and schooling benefits from early childhood interventions focused on improving those development outcomes. The underlying argument is that a child's cognition and certain other skills are largely developed when a child is young, e.g., before reaching the age of 3 years (Grantham-McGregor et al., 2007). If a child is developmentally delayed when young, the delays can persist through school age and into later in life.

In China, an emerging literature has shown that there may be a large share of rural children who experience developmental delays in early childhood. Although studies have found that samples of urban infants and toddlers appear to have normal development (Shi, Shi, Guan, Zhang, & Hu, 2001; Sun, Ren, & Su, 1996; Xie, Wang, & Yao, 2006), the same is not true for rural children. Wang et al. (2018) found that 54% of children in rural mountainous communities; 48% in rural plains communities; and 42% in migrant communities, urban communities where rural families live, are developmentally delayed (< -1 SD). Likewise, testing also shows high levels of language and social-emotional delays (Wang et al., 2018). Assuming that the samples in the studies are representative of large areas of rural China, as the authors argue, this could mean that one of the reasons for the education gaps among rural students is low levels of cognition when they are young (e.g., 0–3 years old). To our knowledge, however, there have not been any studies that empirically assess the role that low levels of cognitive development play among primary school children in the context of the poor educational attainment in rural China.

To address this gap, this study aims to estimate the influence of cognitive development on levels of educational performance of rural elementary school students in China. To meet the study's objectives, we collected data on more than 10,000 Grades 3 and 4 primary school students who were attending 119 schools in migrant and rural communities across China. Specifically, the sample covers 59 private migrant schools in Beijing and Suzhou and 60 public rural schools in the Henan and Anhui Provinces. In addition to collecting data about student and family characteristics and administering students standardized academic achievement tests in math, we used the Raven Standard Progressive Matrices test to measure the level of cognitive ability (or IQ) of the sample students. Using these data, we conduct several empirical exercises. First, we develop a measure of the prevalence of students who suffer from cognitive delays, defined as having an IQ of 1 SD less than the international norm. Second, we identify student and family characteristics that are associated with high versus low levels of IQ. Third, we test the correlation between IQ and student academic performance, while holding constant other factors and controlling for school and class fixed effects. Finally, we examine the magnitude of the coefficients to assess the relative strength of the associations between IQ and other factors and their relationship with student academic performance in math.

The findings of our study indicate that one-third (33%) of students suffer from developmental delay (or low IQ), meaning that the proportion of rural students with developmental delays is more than twice the proportion of that of children from urban populations. The results are robust if we consider children who live with their parents and go to either private migrant schools or rural public schools or if they are left-behind children who are living with a caregiver who is not their parent and who are attending rural public schools. The multivariate analysis then demonstrates that there is a strong and positive relationship between IQ and school performance in math, a finding that is robust to where children go to school and their living arrangements. When examining the strength of the relationship, we found that the association between IQ and school performance is much higher than the relationships between other factors, including attendance of preschool, number of siblings in the home, mother's education, father's education, family wealth, and school performance. Indeed, according to our findings, if two children have IQs that vary by 1 SD, their math scores vary by more than 0.32 SD. When this result is coupled with the high proportion of rural children who are developmentally delayed, we believe that this is evidence that the differences in cognitive outcomes among rural students is an important factor in the education gap between the relatively high- and low-performing rural students.

This study makes several contributions. Although there is research that explore the sources of the gaps in education among rural students, to our knowledge, there is no research that focuses on the role of poor level of cognitive development of rural students. To do this, we first show, in representative samples of rural students that are drawn randomly from schools in two different schooling environments, that large proportions of rural students have cognitive delays. We then show strong correlations, holding a large number of other variables constant, between these levels of delays and the performance of students on a standardized math test. We demonstrate that the strength of the association between cognitive delay and poor academic performance is much stronger than are other determinants of academic performance, such as preschool attendance, family wealth, or parental education. Although future research still needs to focus on fully identifying the causal effect of student cognitive abilities on school performance, the evidence in this paper is sufficiently novel and important to constitute a contribution to the literature.

In reading this paper, we caution the reader with one important caveat. It is possible that other factors, which we have not included in the analysis (such as non-cognitive personality traits), that have been shown to be correlated with IQ and also an explanatory factor for schooling outcomes, may be important (and need to be studied in the future—Borghans, Golsteyn, Heckman, & Humphries, 2016). However, the literature also is clear that "skills begets skills" (Heckman, 2013, page 32). When a child's cognition does not develop fully when a child is young, it affects the formation of non-cognitive skills. Hence, in this sense there is a strong developmental tie between low IQ and poor schooling outcomes.

The remainder of the paper is structured as follows. In Section 2, we introduce the sample and provide descriptive statistics. In Section 3, the levels of cognition of elementary school-aged children are presented, and comparisons are made between three types of students: the children of migrants who are living with their parents and attending school in the cities (*migrant children*), children who are living in rural areas with their parents (children living with their parents, *or CLPs*), and children who are living in rural areas with a relative while their parents live and work in the city (left-behind children, *or LBCs*). In Section 4, we present the estimation strategy for the analysis of the descriptive (univariate) correlates with IQ and the relationship between IQ and educational performance. Section 5 presents the results of the multivariate analysis that measures the conditional relationship between IQ and school educational performance, and, finally, Section 6 concludes the paper.

2. Data and variables

2.1. Sampling

This study uses a cross-sectional dataset that we collected in 2017. The data collection was conducted in two sets of migrant communities, Beijing (in Northern China) and Suzhou (a suburb of Shanghai in Eastern China), as well as in two sets of rural communities in the Henan and Anhui Provinces. Henan is a province from which more migrants travel to Beijing than any other province. Anhui is the largest source of migrants for Suzhou and one of the largest sources of migrants for the Greater Shanghai area, of which Suzhou is a part. In total, the research team surveyed, tested for IQ, and administered standardized math tests to 11,560 primary school students in 59 urban migrant primary schools and 60 rural public primary schools.

To choose the sample, we used a four-step protocol in all of the survey locations. After selecting Beijing and Suzhou as our survey locations, the first step was to put together a list of private migrant schools in both sites. In Beijing, the list was obtained from a non-governmental organization, the Culture Center of Beijing Migrants. In Suzhou, the Suzhou Women and Children's Activity Center provided us with a list of schools. In Beijing, there were 70 schools on the list; in Suzhou, there were 50 schools. Using the list, in the second step of the protocol, we randomly selected 30 schools in Beijing and 30 schools in Suzhou (although, in the end, the enumeration team was able to carry out the procedure in only 29 schools).

The third step entailed choosing the classes and the students in the sample schools. Based on our protocol, we chose one class of Grade 3 students and one class of Grade 4 students. If the school only had one class, we chose that class. If the school had multiple Grade 3 and Grade 4, one class was randomly chosen. The fourth (final) step was to choose the students. All students in the selected class became part of the sample. In total, we chose 60 classes and 1,931 students in Beijing and 58 classes and 3,239 students in Suzhou (Table 1).

The baseline survey was conducted in Beijing and Suzhou two weeks before the surveys were conducted in Henan and Anhui. We established this order (first the migrant schools and then the rural schools) because, during the surveys in Beijing and Suzhou, we were able to identify the home counties of the students in the migrant schools. Using this information in the second part of the survey, in the rural schools in Henan and Anhui, we then were able to choose study sites that were the hometowns of a large proportion of the migrant students. Specifically, after tabulating the results from the survey, we chose the five most-cited Henan counties from the Beijing sample and the five most-cited Anhui counties from the Suzhou sample.

After the counties were chosen, the protocols in Henan and Anhui for choosing the sample schools, classes, and students were mainly the same as those for the migrant schools. Each county's bureau of education provided us with a comprehensive list of rural elementary schools (leaving out schools in the county seat because they were attended mostly by urban children). In the next step, we randomly chose six schools out of each county's list of schools. In total, we chose 30 schools (five counties x six schools per county) in Henan, and we chose 30 schools in Anhui. In the next step, we randomly chose one Grade 3 and one Grade 4 class per school. Finally, all students in each of the sample classes became part of the survey. In total, we chose 60 classes and 3,456 students in Henan and 60 classes and 2,934 students in Anhui.

Selecting our sample this way resulted in three sets of different types of students. All of the students (n = 5,170) in Beijing and Suzhou were *migrant students*. Of those (n = 6,390) in Henan and Anhui, there were 3,109 LBC students and 3,281 CLP students. In our overall sample, 5,718 were Grade 3 students, and 5,842 were Grade 4 students.

Table 1
Sample distribution across the full sample and subgroups/grades.

Subgroup/Grade	All	Migrant children primary school		Rural public primary school	
		Beijing	Suzhou	Henan	Anhui
Migrant children	5,170	1,931	3,239	—	—
Children who live with parents (CLPs)	3,281	—	—	1,861	1,420
Left-behind children (LBCs)	3,109	—	—	1,595	1,514
Grade 3	5,718	925	1,600	1,702	1,491
Grade 4	5,842	1,006	1,639	1,754	1,443

2.2. Survey and variables

In each set of sample schools in the two sample cities and two sample rural provinces, we administered a single set of survey instruments to students. The overall student survey consisted of three main blocks. Specifically, all students completed a cognitive evaluation, a standardized math test, and a questionnaire that elicited personal information about their own characteristics and those of their families.

In the first block of the survey, we evaluated the cognitive skills of the students. To measure cognitive skills, we used the Raven Standard Progressive Matrices test (Raven, 1938), hereafter, the Raven test. The Raven test, originally designed by British psychologist J. C. Raven, is a nonverbal (language-neutral) intelligence test comprised entirely of pictorial questions related to spatial reasoning and pattern matching. The test is a kind of cross-cultural reasoning tool that is divided into five parts, each of which is sorted into 12 questions according to difficulty. The total score on these 60 questions is calculated based on an established norm to assign a final IQ. The Raven test of cognitive skills is one of the most widely used tests in the world (Borghans et al., 2016).

Choosing an appropriate norm is important to compensate for the Flynn effect, a phenomenon in which average IQs for populations rise over time (Liu & Lynn, 2013; Raven, 2000). The version of the test and the original norm that we use came from a 1986 IQ assessment conducted in urban China (Zhang & Wang, 1989). The 1986 IQ assessment was conducted by a group of Chinese psychologists and scholars in the field of education. They carefully followed the protocol of the Raven (Raven, 1938). The version of the Raven used in 1986 in China includes 60 tests in the form of geometric graphs. Based on the sampling of China's 1982 Census, the 1986 IQ assessment include 5,108 individuals in age cohorts from 5.5 to 70 years old in urban China and is considered a valid set of norms for China. We used an older version of this test because there is no newer version available for Chinese populations. A number of studies in China have used the Raven and published the results (Lai, Yin, & Chen, 2016; Li, Luo, Wang, & Xu, 2011; Liu, Zhao, & Dai, 2016; Zhou, Cheng, Li, Han, & Li, 2016). Moreover, although the test was initially normalized in China nearly 30 years ago, such a time span is not unusual. For instance, studies conducted in Japan in the 1990s (e.g., Lynn & Shigehisa, 1991) used norms established by Jensen & Munro (1979) over ten years prior. Nevertheless, we recognize the need to compensate for using a nearly 30-year-old norm in our Raven test. Because Raven test scores generally change at the same rate across cultures and time (Raven, 2000), we adjust our final scores by using the Flynn effect of 6.19, given in a 2013 study of increasing scale norms from 1986 to 2012 (Liu & Lynn, 2013).

In the second block of the student survey, all sample students (11,560) were administered a standardized math test. There was a separate test (30 questions) for Grade 3 and Grade 4 students. The test questions for the standardized math exam were chosen from the Trends in International Mathematics and Science Study (TIMSS) test data bank, but all of the questions were consistent with the curriculum that was being taught in all of the schools. The TIMSS test is one of most common instruments for measuring academic performance for math for primary school students in the world (Mullis et al., 2012) but specifically in China (Tsui, 2007; Zhao, Yu, Wang, & Glauben, 2014).

To generate a variable that we could utilize to measure academic performance, we used the raw data from the math test portion of the survey and turned the data into a set of standardized test scores. To do so, the scores were standardized by scaling them into *z*-scores, which was done by subtracting the mean score and dividing by the standard deviation of the math score distribution of all students in each dataset. The test scores that are used in this study are presented in terms of SDs.

In the third survey block, all students in our sample were asked to answer a series of questions that provided information so that we could produce variables to measure each student's individual and family characteristics. From these questionnaires, we collected data that were used to generate variables, including each student's gender, age (using date of birth), and number of siblings, as well as the level of educational attainment of the student's father and mother, whether the student had ever attended preschool, the ages of each student's parents, whether the father currently drank or smoked, and durable household assets.

We also generated variables from the questionnaire to determine the migration status of each student's parents. During the survey in both private migrant schools and public rural schools, we recorded the migration status of the father and mother for each student since the start of primary school. In the private migrant schools, by definition, all of the students are migrant students. As such, none had an urban *hukou* (household) and, due to this, none was qualified to enroll in an urban public school. For the students in rural public schools (in the Henan and Anhui samples), the information on the migration status of their parents allowed us to identify CLPs and LBCs. As noted, CLPs are those students who are living at home under the care and oversight of one or both of their parents. LBCs, in contrast, are students whose parents have both migrated and who live with their grandparents (or other caregivers). CLPs and LBSs attend rural public schools.

Brown & Park (2002) found that school performance is strongly correlated with household income. In this study, however, we were not able to record income because our survey was one in which the students provided the information. They were, however, able to provide information on the major assets owned by their families. With this information, following an approach proposed by Filmer & Pritchett (2001), we used principle component analysis to create a variable that measured rural durable assets and produced a proxy of household wealth. To implement this part of the survey, we first asked each student about the household's ownership status of seven assets, including refrigerators, televisions, and computers. If a household owned a specific asset, it was recorded as 1; otherwise, 0. Second, by using the principal components analysis, we calculated the scoring factors for seven assets.

Table 2 presents the summary statistics for the variables in the analysis, both for the full sample and for migrant students, LBCs, and CLPs. A number of the variables show that the children in the survey are relatively representative of children across rural China. For example, according to the Sixth National Population census, the gender ratio of the children (proportion of boys to all children) in the same age cohorts of our study is 0.54, which is the same as the gender ratio in our sample (0.54). The mean years of education of the father (8.9) and mother (8.3) in our sample are similar to the levels of education attainment in the census data. When we use the

Table 2
Variables, variable names and summary statistic for sample and for sample subgroups.

Variable	Definition	Total		Migrant students		CLPs		LBCs	
		Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
IQ scores	Flynn adjusted IQ score	88.95	15.15	90.38	14.26	88.50	15.67	87.06	15.75
Low IQ individual	Dummy; 0 = normal; 1 = low	0.33	0.47	0.29	0.45	0.35	0.48	0.38	0.49
Math score	Standard math tests	19.28	4.95	19.55	4.50	19.49	5.19	18.60	5.35
Standardized math score	Stand. math score	0	1	0.06	0.91	0.04	1.05	-0.14	1.08
Gender dummy	Dummy; 1 = boy; 0 = girl	0.54	0.50	0.56	0.50	0.52	0.50	0.54	0.50
Grade dummy	Dummy; 1 = 4th; 0 = 3rd	0.51	0.50	0.51	0.50	0.50	0.50	0.50	0.50
Age months	Age measured by month	126.64	10.64	126.85	10.55	126.2	10.66	126.7	10.76
Preschool	Dummy; 1 = attended preschool; 0 = not	0.92	0.27	0.89	0.31	0.95	0.23	0.93	0.26
Number of siblings	The number of siblings	0.47	0.63	0.43	0.60	0.54	0.65	0.46	0.63
Father's age	Age of father	37.64	1.51	38.30	1.22	37.17	1.51	37.05	1.52
Mother's age	Age of mother	35.95	1.22	36.24	1.11	35.79	1.23	35.62	1.28
Father's education	Educational years of father	8.91	2.73	9.32	2.69	8.57	2.78	8.60	2.67
Mother's education	Educational years of mother	8.32	3.33	8.75	3.21	7.89	3.42	8.06	3.32
Father smokes	Dummy; 1 father smokes; 0 = not	0.56	0.50	0.56	0.50	0.54	0.50	0.57	0.50
Father drinks	Dummy; 1 father drinks; 0 = not	0.66	0.48	0.65	0.48	0.66	0.47	0.67	0.47
Household assets	Household durable asset index	0.00	1.26	0.07	1.38	0.01	1.16	-0.12	1.11
No. of observations		11,560		5,170		3,281		3,109	

Data Source: Author's survey.

education levels of rural individuals who are in the 35–39-year age cohorts in rural areas, these ratios are 8.0 for men and 7.1 for women.[1]

Table 2 also allows us to make comparisons among the students in the different subgroups of our sample, i.e., among the migrant children, LBCs, and CLPs. Our data show that migrant students exhibit a somewhat lower preschool attendance rate (89%) than do rural students (94%). In contrast, the mean years of education of the parents of migrant students (9.3 for fathers; 8.8 for mothers) are marginally higher than those for the parents of rural students (8.6 for fathers; 8 for mothers). All other characteristics are nearly the same (or the differences are statistically insignificant).

3. Descriptive statistics: IQ and math test scores

3.1. Distribution of student IQ

Table 3 presents the descriptive statistics for the levels of cognitive development of the students. The results indicate that, after the Flynn adjustment, the mean IQ score is 89.0. Given that the mean of the normed distribution is 100 and the standard deviation is 15, the proportion of the children in our sample who are developmentally delayed (with an IQ of less than 85, or –1 standard deviation) is 33.3%. Using the same data, Fig. 1 shows the distribution of the Raven scores, which are positioned to the left of the normed distribution. The distribution is also slightly skewed to the left, meaning that there are fewer students who have higher levels of cognition and more who have lower levels of cognition.

As seen in Table 3, when dividing the Raven score distributions among migrant children, CLPs, and LBCs, the data show a clear order. Although the mean Raven score of the full sample is 89.0, migrant children scored 90.4, on average. The results in the second column show that the proportion of migrant children with developmental delays is 29%. Although still high relative to a sample of children with normal levels of cognition, this rate of developmental delay is lower than the sample mean (33.3%). In contrast, LBCs scored lower (87.1) than the sample mean (89.0). The proportion of LBCs who show developmental delays (38.5%) is higher than the mean (33.3%), while CLPs are in between. The mean Raven score of CLPs is 88.5 (0.5 points lower than the sample men), and 35.1% of CLPs show signs of developmental delay.

Although the results in Table 4 show that there are differences among the subgroups, graphical illustrations of the distributions demonstrate that, in fact, the studied populations are all vulnerable. Panels A, B, and C of Fig. 2 show the relative positions of the IQ distributions of migrant students, CLPs, and LBCs, respectively. Most notably, the three panels illustrate that the distributions of the Raven scores of the three subgroups of sample students are all clearly positioned to the left of the normed distribution. This is consistent with the cognition distribution of the full sample in Fig. 1. Further, close inspection of the three panels in Fig. 2 shows that there are slight differences in the degree to which they are positioned to the left of the distribution that characterizes normal/healthy populations. Nevertheless, they are more similar than different, which means that there are nearly equal (and relatively high)

[1] To check the representativeness of our data, we compare our data with data from the representative data sets that the reviewer suggested, including Rural-Urban Migration in China and the China Labor-force Dynamics Survey. In total, our data and the data from these two national representative data sets have for four key variables that overlap (or are found in all three datasets): mother's age, father's age, education level of the mother, and education level of the father. According to our findings (comparison tables available from authors upon request), students and their families from our data set are quite representative of rural students and migrant students across China.

Table 3
IQ distribution of students by iq in full sample and subgroups

IQ Index	All	Subgroup				
		Migrant	CLPs	LBCs	(2)–(4)	(3)–(4)
	(1)	(2)	(3)	(4)		
IQ scores	88.95	90.36	88.49*	87.06*	3.30*	1.43*
Low IQ individual	33.3%	29.0%	35.1%	38.5%	-9.5%*	-3.4%*

* p < .01.

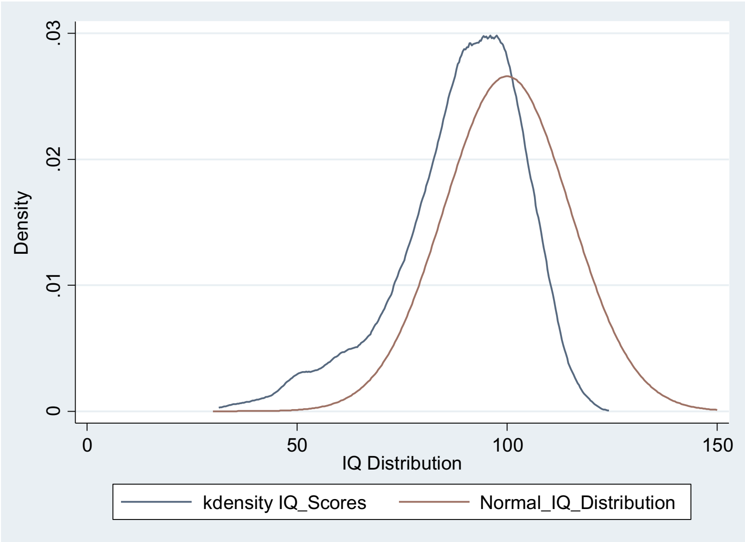


Fig. 1. Distribution of IQ scores for full sample and normal IQ distribution (Mean = 100, Standard deviation = 15).

Table 4
Descriptive analysis of iq scores among different types of students

Variable		Obs.	Mean IQ score	Difference between groups
Gender dummy	Boy	6,257*	88.6*	−0.8*
	Girl	5,303	89.4	
Preschool	Yes	10,608	89.5	6.8*
	No	952	82.7	
Only child	Yes	6,991	90.2	2.8*
	No	4,569	87.0	
Father's education	Less than 9 years	4,060	86.7	−3.5*
	At least 9 years	7,500	90.2	
Mother's education	Less than 9 years	5,304	87.4	−2.9*
	At least 9 years	6,256	90.3	
Father smokes	Yes	6,417	88.2	−1.7*
	No	5,143	89.9	
Father drinks	Yes	7,581	88.6	−1.1*
	No	3,979	89.7	
Household assets	Low	4,387	87.7	−2.0*
	High	7,173	89.7	

* p < .01.

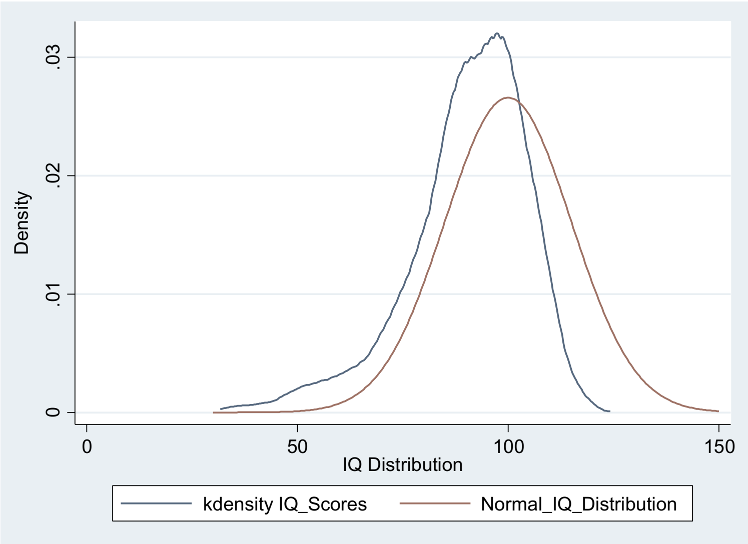
proportions of developmentally delayed students in all three subpopulations.

Table 4 presents the results for tests of the differences in cognition scores associated with student and family characteristics. Our results show that, on average, cognition is 0.8 points higher for boys than it is for girls (p < .001). There are also statistically significant differences in the Raven scores between those who had attended preschool and those who had not. Being a single child in a family, on average, is associated with a score of 3.29 points higher as compared to the scores of those children with siblings. These results also indicate that students from wealthier households, homes with fathers who do not smoke, and homes with fathers who have higher levels of education demonstrate higher levels of cognition.

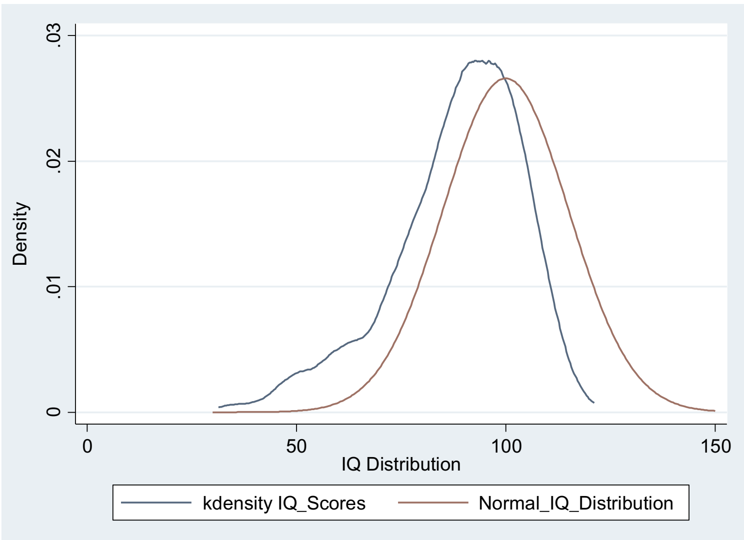
3.2. Distribution of educational performance

The math scores of the sample students are shown in Table 2, with an overall mean score of 19.28. Although this score, on its own, does not tell us anything, when we compare the math scores among the study's subgroups, the relative levels of the scores display a similar pattern to that of the relative levels of the Raven scores. Specifically, the mean math score of migrant children is 19.55, which is 0.06 SD above the overall sample mean. In contrast, the mean math scores of LBCs (18.60) are lower than the overall mean (0.14 SD below the mean and 0.20 SD below the mean scores of migrants), and the scores of CLPs (19.49) are in the middle. Thus, when comparing mean math scores among the three subpopulations, the relative order of the math scores mirror those of the Raven scores.

Fig. 3 presents the kernel density distribution of standardized math scores of the full sample. It is useful to compare the distributions below with those of the Raven scores for the overall sample in Fig. 1. Specifically, both figures are clearly skewed to the left, meaning that there are relatively more students in our sample who are developmentally delayed.

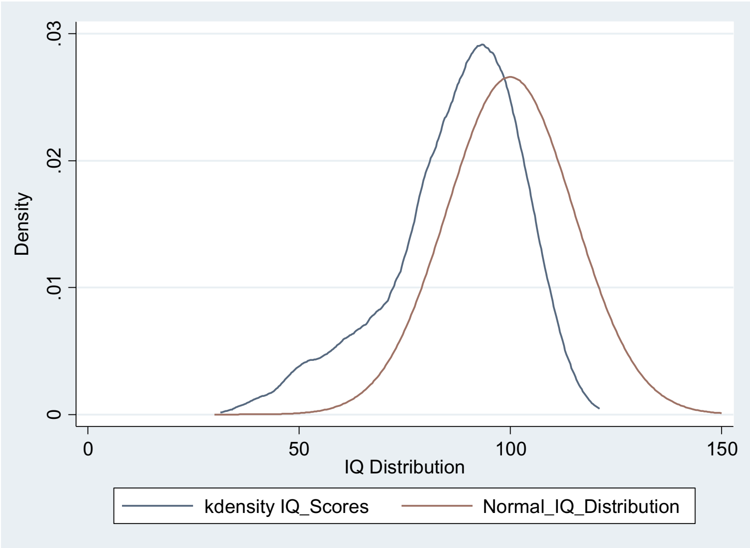


Panel A: Migrant Student IQs



Panel B: CLP student IQs

Fig. 2. Distribution of IQs for subgroups and normal IQ distribution (Mean = 100, Standard deviation = 15).



Panel C: LBC student IQs

Fig. 2. (*continued*)

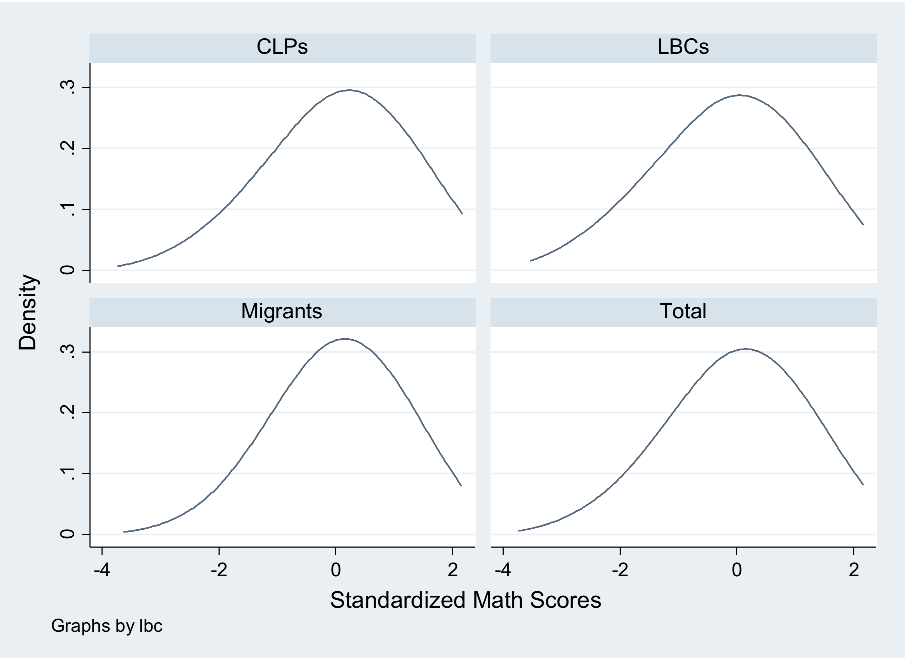


Fig. 3. Kernel density distributions of standardized math scores for full sample and for subgroups.

3.3. Correlates of student IQ and educational performance

Fig. 4 illustrates the relationship between student IQ and educational performance measured by standardized math scores. The IQ scores are on the *x*-axis, and the math scores are on the *y*-axis. Panel A presents the full sample. Panels B to D present the samples for the different subgroups.

According to the findings, the math scores and the Raven scores are highly correlated. The upward sloping line in the figures shows that math scores are associated positively with IQ. Using the full sample, the correlation coefficient is 0.54, indicating a strong relationship. The nature of the association between IQ and math is also large in magnitude. Students with Raven scores of approximately 80 (–1.3 SD) have math scores that are approximately 1 SD lower than those of a student with an IQ of 100.

The relationships between student IQ and math scores are similar for all of the subgroups (Panels B to D); the lines are all upward sloping. The correlation coefficients are all high, ranging from 0.49 for the migrant subgroup to 0.58 for CLPs, and the correlation coefficient for LBCs is 0.56. These figures support the hypothesis of Heckman (2013) that higher IQs, which are largely created when children are young, are associated with better educational performance.

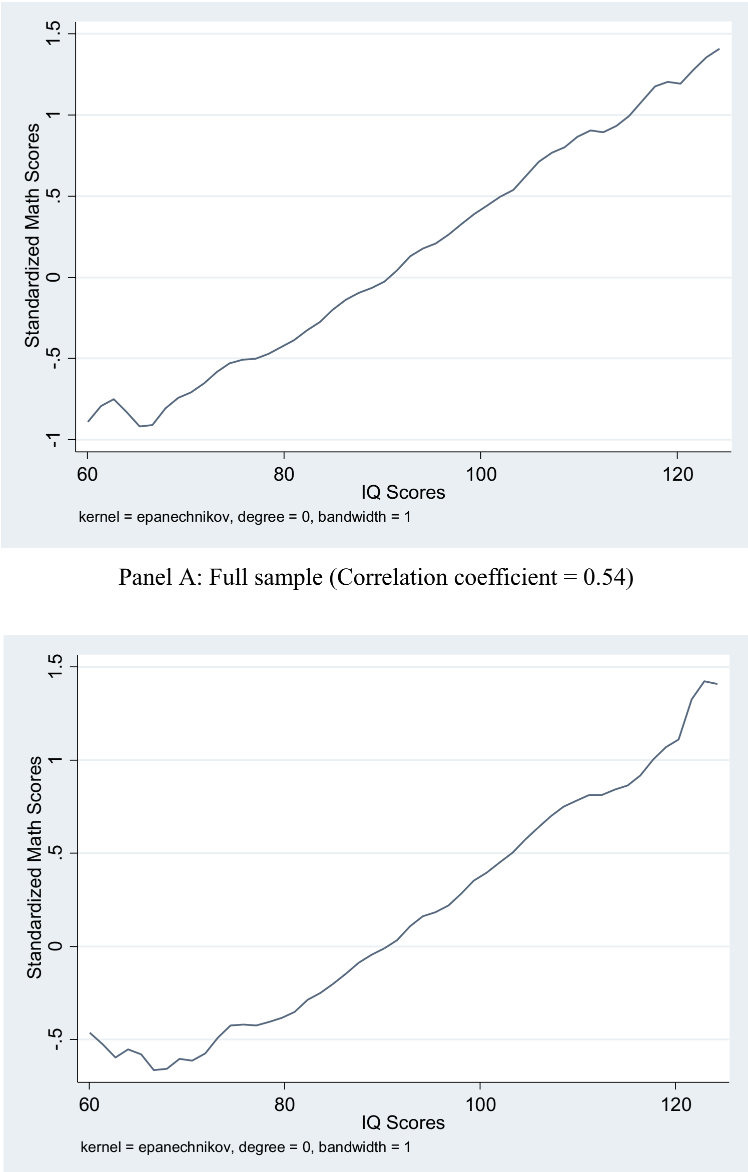
4. Multivariate regression analysis approach

4.1. Correlates of IQ

As a starting point of the analysis, we use a statistical model that estimates the relationship between IQ and the personal and household characteristics:

$$IQ_{ij} = \alpha_0 + \beta X_{ij} + \gamma Sch_j + \varepsilon_{ij}, \quad (1)$$

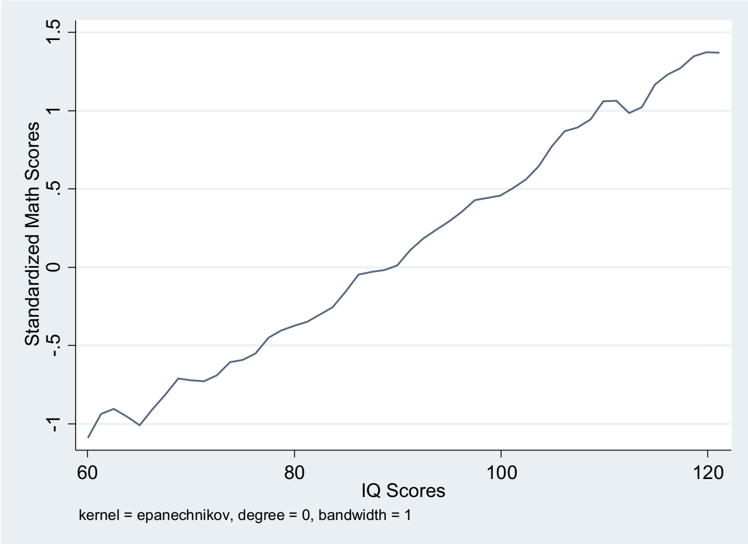
where IQ_i denotes the cognition of the students. The vector X_{ij} is comprised of a set of factors designed to capture the part of the



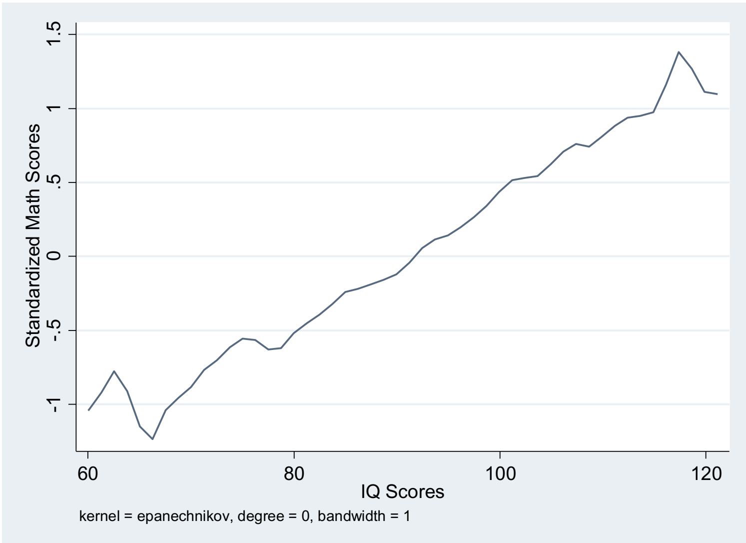
Panel A: Full sample (Correlation coefficient = 0.54)

Panel B: Migrant Students (Correlation coefficient = 0.49)

Fig. 4. Kernel density plots of correlations between IQ scores and standardized math scores of full sample and subgroups.



Panel C: CLP students (Correlation coefficient = 0.58)



Panel D: LBC students (Correlation coefficient = 0.56)

Fig. 4. (*continued*)

variation in IQ_{ij} that is due to observable student and family characteristics. Factors in X_{ij} include gender, number of siblings, education level of both parents, age of both parents, and household assets. Eq. (1) also controls for school fixed effects, denoted Sch_j. The symbol β is a vector of coefficients that measure the correlation of personal and family characteristics with IQ_{ij}. The term α_0 is the intercept, and ε represents random error that exists in a normal distribution. Here, i represents each of the student observations, and j represents each school.

4.2. Relationship between IQ and educational performance

One of the important objectives of this study is to link the educational performance of the students with their cognition level, controlling for observable personal and family characteristics. Multivariate regression analysis of IQ and educational performance is conducted in the following steps. First, we run an ordinary least squares model, controlling for student and family characteristics. Then, we add the school effects because student achievement also may be correlated with the quality of school facilities and teaching resources.

We first specify the OLS model as follows:

$$y_i = \alpha_0 + \beta IQ_i + \gamma X_i + \varepsilon_i, \tag{2}$$

where y_i denotes the standardized math test score, and IQ_i denotes the cognition of the students. The coefficient β is the coefficient we are interested in because it measures the correlation between IQ_i and student educational performance. The vector X_i is defined in the same way as the variables were in Eq. (1), and γ is the related coefficient vector. As above, α is the intercept, and ε is random error that exists in a normal distribution. Here, i represents each of the observations.

The second model is similar as above, but in it we add school effects:

$$y_{ij} = \alpha_0 + \beta IQ_{ij} + \gamma X_{ij} + \delta Sch_j + \varepsilon_{ij,} \tag{3}$$

where y denotes each student's standardized math test score, and IQ_{ij} denotes the cognition of the students. All other control variables remain the same as in Eq. (2). Sch_j represents a vector of school dummy to capture the school effects.

Because Raven scores are sensitive to age in days, we perform a robustness analysis, using the same model as in Eq. (3), to measure the relationship between math score and IQ for the subgroups comprised of students who took the Raven tests that were scored by the same scoring protocol and who were in the same grade level (Grade 3 or Grade 4). Given that our survey date was in May or shortly thereafter, one of the subsamples is comprised of the students who were born between November 1, 2008, and May 1, 2009 (were between 8 years and 8-1/2 years old at the time of our survey), and were in Grade 3. The other group comprises those students who were born between November 1, 2007, and May 1, 2008 (were between 9 years and 9-1/2 years old), and were in Grade 4. Although the sample sizes for this analysis are smaller, these two subsamples were the most well-defined subgroups in which we could examine the relationship between IQ and math score.

5. Results

5.1. Multivariate regression results of IQ

The results in Table 5 show the relationship between IQ scores and the characteristics of the full sample and subgroups. Our

Table 5
Multivariate analysis of correlates of iq scores (dependent variable of interest) and individual and family characteristics (independent variables) for overall sample and sample subgroups.

Variable Names [a]	All	Sample Subgroups [b]		
		Migrant	CLPs	LBCs
	(1)	(2)	(3)	(4)
Gender dummy	−0.526*	−0.843**	−1.219**	1.071*
	(0.276)	(0.397)	(0.535)	(0.564)
Preschool	5.909***	6.273***	7.319***	5.486***
	(0.503)	(0.640)	(1.167)	(1.079)
Number of siblings	−1.543***	−1.979***	−1.493***	−1.315***
	(0.222)	(0.333)	(0.412)	(0.451)
Father's age	9.084	−0.469	−0.499	0.484
	(8.206)	(0.298)	(1.952)	(2.841)
Mother's age	−5.821	0.066	−0.339	−2.744
	(6.603)	(0.327)	(4.825)	(7.147)
Father's education	0.189***	0.234***	0.295***	0.031
	(0.055)	(0.081)	(0.104)	(0.113)
Mother's education	0.052	0.003	0.154*	0.054
	(0.046)	(0.068)	(0.087)	(0.092)
Household assets	0.347***	0.170	0.849***	0.249
	(0.111)	(0.143)	(0.236)	(0.257)
Father smokes	−1.428***	−1.609***	−1.668***	−1.301**
	(0.297)	(0.428)	(0.567)	(0.610)
Father drinks	−0.414	0.055	−0.839	−0.436
	(0.311)	(0.445)	(0.598)	(0.647)
School effects	yes	yes	yes	yes
Constant	−44.610	100.309***	111.227	162.643
	(74.117)	(6.758)	(114.456)	(178.696)
Observations	11,560	5,170	3,281	3,109
R-squared	0.100	0.040	0.121	0.090

Data Source: Author's survey.
Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[a] For definition of Variables see Table 2.
[b] The three sample subgroups are defined in note "b" in Table 2.

Table 6
Multivariate analysis of correlates of low IQ individual scores and individual and family characteristics for full sample and subgroups.

Variable	All	Subgroup		
		Migrant	Non-left	Left
Gender dummy	0.024***	0.043***	0.037**	−0.023
	(0.009)	(0.013)	(0.017)	(0.018)
Preschool	−0.135***	−0.127***	−0.153***	−0.135***
	(0.016)	(0.021)	(0.036)	(0.034)
Number of siblings	0.034***	0.041***	0.040***	0.019
	(0.007)	(0.011)	(0.013)	(0.014)
Father's age	−0.349	−2.130	−0.018	0.081
	(0.260)	(1.635)	(0.061)	(0.089)
Mother's age	0.243	1.236	0.127	−0.039
	(0.209)	(0.955)	(0.150)	(0.224)
Father's education	−0.006***	−0.007***	−0.009***	−0.003
	(0.002)	(0.003)	(0.003)	(0.004)
Mother's education	0.001	0.003	−0.001	−0.001
	(0.001)	(0.002)	(0.003)	(0.003)
Household assets	−0.010***	0.000	−0.028***	−0.014*
	(0.004)	(0.005)	(0.007)	(0.008)
Father smokes	0.025***	0.022	0.031*	0.024
	(0.009)	(0.014)	(0.018)	(0.019)
Father drinks	0.009	0.009	0.021	−0.005
	(0.010)	(0.014)	(0.019)	(0.020)
Constant	4.657**	36.001	−3.378	−1.052
	(2.348)	(27.146)	(3.548)	(5.595)
Observations	11,560	5,170	3,281	3,109
R^2	0.066	0.053	0.089	0.064

Data Source: Author's survey.
Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[a] Low IQ Individuals include all students with IQ less than -1 Standard Deviations.
[b] For definition of Variables see Table 2.
[c] The three sample subgroups are defined in note "b" in Table 3.

results show that the cognitive development of the students in the overall sample and the subgroups is negatively correlated with the number of siblings. Specifically, for every additional sibling a child has, the child's IQ, conditional on holding constant other individual and family characteristics, decreases by 1.54 points. Although we do not know the source of this negative relationship in our sample, the literature suggests that the negative number-of-siblings impact is likely to be driven by the effect of resource diffusion across families with multiple children (Blake, 1981, 1989). The results also show that, in families in which the father smokes, the IQ scores of the children are lower, a finding that also is supported by the literature (Farkas, Distefan, Chi, & Peirce, 1999; Powell & Chaloupka, 2005).

In contrast, in families in which the child went to preschool, the father is better educated (except for LBCs), the household has more assets (except for LBCs), and the IQ of the child is higher. The results related to going to preschool are particularly striking; when comparing children who have been to preschool with those who have not, on average, there is a 5.91-point difference. That preschool education has a relatively large impact on the human capital outcomes of children is a common finding in the development literature (Duncan & Magnuson, 2013; Walters, 2015). Given the very high proportion of young children who attend preschool (more than 90%; see Table 2), it may be the case in this study that we are observing, at least in part, reverse causality; that is, children who have low IQs have not gone to preschool.

Interestingly, in the cases of the full sample and of the migrant and CLP families, boys have lower IQs. Among LBCs, however, boys have higher IQs. The higher IQ of girls (in families in which the child almost always lives with his or her parents, which is the case in all migrant and CLP families) is consistent with the results found in developed countries: Girls often have a higher IQ than do boys (Killgore & Schwab, 2012; Oleson & Chappell, 2012). One potential reason for the higher IQ of boys in LBC families is that LBCs usually live with grandparents, and, in such families, there may be a stronger tradition of son- or male-preference, which may induce rural grandparents to invest differently in the health and education of boys versus girls.

For robustness purposes, we also look at the correlates of children who have low IQs (less than –1 SD). The results are shown in Table 6. As seen in the table, the results are similar to those seen in Table 5, when IQ is measured as a continuous variable.

5.2. Correlation analysis of IQ and educational performance

To gain a deeper understanding of the correlation between IQ and educational performance, as one of the main objectives of this paper, we estimate two equations—Eq. (2) (without school fixed effects) and Eq. (3) (with school fixed effects). As seen in Table 7, the results show a strong and positive relationship between IQ and school performance (in our case, scores on a standardized math test). Our findings indicate that, for every one-point gain in IQ, math scores rise by 0.032 to 0.034 SD. When using class fixed effects and

Table 7

Multivariate analysis of correlates of iq scores and standardized math scores: regression models without and with school fixed effects

Variable	Without school fixed effects	With school fixed effects	With class fixed effects
IQ score	0.034***	0.032***	0.032***
	(0.001)	(0.001)	(0.001)
Gender dummy	0.034**	0.024	0.022
	(0.016)	(0.015)	(0.015)
Preschool	0.248***	0.191***	0.190***
	(0.028)	(0.028)	(0.027)
Number of siblings	−0.094***	−0.072***	−0.069***
	(0.013)	(0.012)	(0.012)
Father's age	−0.039***	0.486	1.038*
	(0.010)	(0.449)	(0.619)
Mother's age	0.082***	−0.403	−0.831*
	(0.013)	(0.362)	(0.498)
Father's education	0.010***	0.008***	0.009***
	(0.003)	(0.003)	(0.003)
Mother's education	0.008***	0.008***	0.007***
	(0.003)	(0.003)	(0.002)
Household assets	0.023***	0.013**	0.015**
	(0.006)	(0.006)	(0.006)
Father smokes	−0.077***	−0.064***	−0.057***
	(0.017)	(0.016)	(0.016)
Father drinks	−0.024	−0.035**	−0.029*
	(0.018)	(0.017)	(0.017)
School effects	No	Yes	Yes
Class effects	No	No	Yes
Constant	−4.836***	−6.544	−11.493**
	(0.233)	(4.058)	(5.560)
Observations	11,560	11,560	11,560
R^2	0.311	0.381	0.408

Data Source: Author's survey.

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[a] For definition of Variables see Table 2.

school fixed effects, the results are similar. In both of those columns, the coefficients for IQ are 0.032. These results are consistent with those presented in Fig. 4.

The results in Table 7 suggest that there may be large gains to be made in school performance for children who differ in IQs. For example, assuming the relationship is linear (see Fig. 4), the difference in math test scores of a student with an IQ of 85 and a student with an IQ of 100 is approximately 0.5 SD. In other studies that use the same math testing materials (Koedel & Betts, 2007; Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004), a 0.5 SD represents between one semester and one year of learning. In a competitive schooling system similar to that in China, if one student falls a half-year or more behind his or her cohort (of students with normal IQs), it almost certainly will be difficult to catch up, not even considering the developmental delays that have affected learning in the past and continue to affect the learning that would be needed to catch up.

Caution needs to be exercised at this point to not fully attribute causality to these results. According to Heckman (2013), skills begat skills. In other words, when a child was young, if nutrition or the absence of stimulation led to low levels of cognition, there is also a possibility that that same child's non-cognitive abilities also would be delayed. In Borghans et al. (2016) it is shown in samples of developed countries that both IQ and non-cognitive skills (or personality) are correlated with academic achievement. Hence, if that is the case here, the effect of IQ could be picking up the effect of other non-measured factors that correlated with IQ.

Perhaps, not surprisingly, given the high correlation between IQ and school performance, in the model that accounts for school fixed effects, there is a strong similarity between the variables that are significant in explaining IQ and the variables that are significant in explaining school performance. Specifically, preschool attendance, the education levels of parents, and the family's asset holdings are positively associated with math scores. In contrast, the number of siblings and the smoking and drinking habits of a child's father are negatively correlated with math scores.

5.3. Comparison of the effect of IQ and other factors on academic performance

In this subsection, we demonstrate the strength of the correlation between IQ and academic performance relative to other factors that may be affecting academic performance. In simplest terms, the purpose of this analysis is to help give insights into the question: "How important is IQ in explaining education performance, relative to other factors?" To begin to answer this question, we examine at how 1 SD shifts in each of the explanatory variables are associated with different shifts in academic performance. The explanatory variables that we compare to IQ include preschool attendance, the number of siblings, parental education, and household wealth. For example, 1 SD difference in preschool attendance accounts for a 0.05 SD in academic performance. A 1-SD difference in the number of sibling accounts for a 0.04 SD in academic performance. A 1 SD difference in father's education (0.02 SD), mother's education

Table 8
Multivariate analysis of correlates of iq scores and standardized math scores for subgroups of grades 3 and 4 students.

Variable	Grade 3	Grade 4
IQ score	0.031***	0.033***
	(0.001)	(0.001)
Gender dummy	0.038	0.011
	(0.032)	(0.031)
Preschool	0.141**	0.238***
	(0.058)	(0.064)
Number of siblings	−0.108***	−0.042
	(0.026)	(0.026)
Father's age	0.187	1.641*
	(0.925)	(0.902)
Mother's age	−0.170	−1.444**
	(0.748)	(0.724)
Father's education	0.011*	0.016**
	(0.006)	(0.006)
Mother's education	0.012**	0.004
	(0.005)	(0.005)
Household assets	0.014	0.010
	(0.014)	(0.012)
Father smokes	−0.106***	−0.069**
	(0.035)	(0.033)
Father drinks	−0.067*	0.004
	(0.037)	(0.035)
School effects	Yes	Yes
Constant	−3.497	−11.996
	(8.194)	(8.186)
Observations	2,502	2,742
R^2	0.419	0.426

Data Source: Author's survey.
Note: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
[a] Subgroup for this analysis includes all students whose birth month between November 1st and May 1st.
[b] For definition of Variables see Table 2.

(0.03 SD), and household wealth (0.02 SD) all are associated with less than a 0.05 SD shift in academic performance. In contrast, a 1 SD difference in IQ is associated with a difference in math performance of 0.45 SD.

When looked at this way, then, the importance of IQ in explaining school performance may be put into a clearer perspective. If we improved IQ of students by 1 SD, according to the findings, math performance would almost rise by 0.45 SD. In contrast, if we improved five variables (preschool attendance, the number of sibling, father's education, mother's education and household wealth) each by 1 SD, we would get a rise in math performance of less than 0.45 SD (only 0.16 SD).

5.4. Robustness check

We conduct three robustness checks in regard to the correlations between IQ and school performance. First, we look at subgroups that are of similar ages. Second, we look at differences in the IQ-math score relationship for the different subgroups: migrant children, CLPs, and LBCs. Finally, we examine the associations between IQ and math scores for those children with relatively normal IQs (from –1 SD and above) and for those children with developmental delays (those with IQs less than –1 SD).

As noted in Section 4.2, because the Raven scores are sensitive to age in days, we perform a robustness analysis, using the same model as in Eq. (3), to measure the relationship between math scores and IQ for the subgroups of students who took the Raven test who were scored by the same scoring protocol and who were in the same grade level (Grade 3 and Grade 4, run separately). The results presented in Table 8 suggest that the coefficients were almost perfectly consistent with the estimation when the full sample was used. In Grade 3, a 1-point increase in IQ was associated with a 0.031 SD increase in math scores ($p < .001$). In Grade 4, a 1-point increase in IQ was associated with a 0.033 SD increase in math scores ($p < .001$).

When analyzing the associations between IQ and math scores for the study's three subgroups, we determine that the results are highly consistent with the results for the full sample (Table 9). The results show that, as IQ rises for migrant students, math scores rise by 0.028 SD. The correlations are similar, albeit slightly higher, among CLPs (0.035 SD) and LBCs (0.034 SD). Statistical tests of significance between the subgroups illustrate that the magnitudes of the coefficients are statistically indistinguishable between the CLPs and the migrant children as well as the LBCs and the migrant children (0.006 SD). For the CLPs and LBCs, there are no significant differences.

The correlations between IQ and math also are strong among students who have normal levels of IQ (from –1 SD and above) and those with lower IQs (< -1 SD). For those with relatively normal IQs, math scores rise by 0.04 SD for every IQ point. For those with

Table 9
Multivariate analysis of correlates of iq scores and standardized math scores for overall sample: regression model with school fixed effects for different types of students

Variable	Subgroup			Students by IQ Score	
	Migrant	CLPs	LBCs	Normal IQ	Low IQ
IQ score	0.028***	0.035***	0.034***	0.040***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender dummy	0.030	−0.015	0.056*	0.023	0.024
	(0.022)	(0.029)	(0.031)	(0.017)	(0.029)
Preschool	0.190***	0.184***	0.219***	0.168***	0.228***
	(0.036)	(0.063)	(0.059)	(0.035)	(0.045)
Number of siblings	−0.092***	−0.046**	−0.083***	−0.064***	−0.096***
	(0.018)	(0.022)	(0.024)	(0.014)	(0.023)
Father's age	3.723	−0.108	0.188	0.486	0.184
	(2.800)	(0.106)	(0.154)	(0.534)	(0.803)
Mother's age	−2.119	0.147	−0.898**	−0.429	−0.128
	(1.635)	(0.261)	(0.387)	(0.430)	(0.645)
Father's education	0.009**	0.000	0.012**	0.005	0.013**
	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)
Mother's education	0.012***	0.007	0.001	0.005*	0.011**
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)
Household assets	0.014*	0.012	0.012	0.008	0.022*
	(0.008)	(0.013)	(0.014)	(0.007)	(0.011)
Father smokes	−0.065***	−0.045	−0.082**	−0.045**	−0.104***
	(0.023)	(0.031)	(0.033)	(0.018)	(0.032)
Father drinks	−0.013	−0.058*	−0.045	−0.048**	0.004
	(0.024)	(0.032)	(0.035)	(0.019)	(0.034)
School effects	Yes	Yes	Yes	Yes	Yes
Constant	−66.645	−4.432	22.120**	−6.172	−4.780
	(46.469)	(6.190)	(9.686)	(4.766)	(7.513)
Observations	5,170	3,281	3,109	7,725	3,835
R^2	0.306	0.426	0.432	0.261	0.253

* $p < .10$.
** $p < .05$.
*** $p < .01$.

lower IQs, the correlations between IQ and math scores are still significant (0.023, $p < .001$). Such findings suggest the importance of policies that promote programs to stimulate infants and toddlers in subpopulations that are known to have high rates of developmental delay.

We also conduct additional regressions for the subgroups: single child, students with one sibling, and those with two siblings. The results, presented in Table 10, show strong similarities between the subgroups (single child, students with one sibling, and those with two siblings) and the full sample. For the full sample, math scores rise by 0.032 SD for every IQ point. For the single child, students with one sibling, and those with two siblings, the correlations between IQ and math scores are 0.032 SD, 0.033 SD, and 0.034 SD, respectively.

If a program could raise a child's IQ from 80 to 90, the child's rate of learning math could increase significantly (by approximately 0.25 SD). The entire literature on early childhood development is about the importance of investment during the first three years of a child's life (Gabriella, Heckman, & Pinto, 2016; Heckman, Moon, Pinto, Savelyev, & Yavitz, 2010; Heckman & Raut, 2016; Hoddinott, Maluccio, Behrman, Flores, & Martorell, 2008; Lu & Black, 2016). During a child's first 1,000 days, the brain has the greatest ability to be influenced by positive environmental interventions. Although many positive interventions can occur during compulsory education, it is almost too late to have any substantial impact on cognitive development.

Furthermore, we also tested the correlation of each student's IQ score with his/her standardized math score for students in the three subgroups of our overall sample, including migrant students and CLPs; migrant students and LBCs; and CLPs and LBCs (Appendix Table A1). The results indicate that IQ scores are indeed significantly correlated with student academic performance and that this result is robust across the three subgroups.

6. Discussion and conclusion

Despite the great progress that China has made in developing a modern education system, including in large parts of rural China, the education of rural children and youth is still decidedly mixed (Zhang et al., 2018). Although the literature has focused on trying to explain why some rural students are doing well and others are not (Bai et al., 2018; Chen & Feng, 2013; Wang et al., 2011; Wang et al., 2017), until recently, little attention has been paid to the role that low cognitive development (and associated development delays) plays in the context of poor educational attainment. To address this gap, this study focused on estimating the influence of cognitive development on different levels of educational performance of rural elementary school students in China. By analyzing the

Table 10
Multivariate analysis of the differences for the correlates of iq scores and standardized math scores among subgroups.

Variable	Full sample	Only child	With one sibling	With two siblings
IQ score	0.032***	0.032***	0.033***	0.034***
	(0.001)	(0.001)	(0.001)	(0.002)
Gender dummy	0.024	0.050***	−0.014	−0.007
	(0.015)	(0.019)	(0.028)	(0.069)
Preschool	0.191***	0.166***	0.214***	0.112
	(0.028)	(0.038)	(0.045)	(0.103)
Number of siblings	−0.072***			
	(0.012)			
Father's age	0.486	−0.017	0.883	1.388
	(0.449)	(0.604)	(0.767)	(1.557)
Mother's age	−0.403	-0.036	−0.698	−0.988
	(0.362)	(0.485)	(0.617)	(1.285)
Father's education	0.008***	0.014***	−0.002	0.010
	(0.003)	(0.004)	(0.005)	(0.012)
Mother's education	0.008***	0.009***	0.008*	−0.003
	(0.003)	(0.003)	(0.004)	(0.009)
Household assets	0.013**	0.014*	0.007	0.038
	(0.006)	(0.008)	(0.011)	(0.024)
Father smokes	-0.064***	-0.041**	-0.097***	-0.121*
	(0.016)	(0.020)	(0.030)	(0.068)
Father drinks	-0.035**	-0.045**	-0.043	0.065
	(0.017)	(0.021)	(0.031)	(0.074)
School effects	Yes	Yes	Yes	Yes
Constant	-6.544	-1.075	-10.690	-18.813
	(4.058)	(5.442)	(7.015)	(13.131)
Observations	11,560	6,991	3,748	821
R^2	0.381	0.361	0.413	0.482

* $p < .10$.
** $p < .05$.
*** $p < .01$.

data of more than 10,000 primary school students from private migrant schools in Beijing and Suzhou and public rural schools from the Henan and Anhui Provinces, we demonstrate, using the Raven, that there are high rates of developmental delay (measured levels of cognition of at least -1 SD relative to international norms) in rural schools. Specifically, the empirical analysis found that approximately 33% of the sample rural students had test results that indicated a developmental delay. The results also suggest that the cognitive development of students is highly correlated with their educational performance. Specifically, for every one- (10-) point gain in IQ, math scores rise by 0.033 (0.33) SD.

In this study, the schools included students who live different subregions of China's rural communities. Approximately half of our sample students lived in and attended schools in migrant communities. The other half were children who lived in rural areas and attended rural public schools and included both LBCs and CLPs. The findings indicate that, although there were small differences in the rates of delay and the levels of educational performance among the migrant students, LBCs, and CLPs, all of these subgroups are at risk for cognitive delay, and the delays are highly correlated with poor educational performance. These findings partly address the concern that we examined only certain samples. Because all of the students experience delays that are nearly the same, our sample selection did not bias the results.

The findings of this paper are similar to those of Heckman and Mosso (2014), who show that the home environment determines early childhood outcomes and that these outcomes can persist throughout one's life. Using the results of the regression that examined the correlations between variables that measured different types of students and their families and IQ, we show that children (families) who do not attend preschool, have more siblings, have parents with lower levels of education, and have fewer household assets are more likely to suffer from developmental delays.

There are two ways that the information can be used. First, it is clear that the government cannot change the IQ of the children who are already students in primary school (as IQ is more or less set for life for an individual by 3 years old or shortly thereafter; Attanasio, 2015; Lu & Black, 2016). However, education systems can use information on the vulnerability of certain groups of primary school students to target remedial programs to those who are more vulnerable and who need more help in school. In other words, the educational system could use our study's results to help them identify types of students who might have special education needs.

Second, since it is impossible to change the IQs of school-aged children, it still is possible to intervene through programs for infants and toddlers (and preschool aged-students) that improve nutrition (e.g., programs that teach parents about better feeding practices) and parenting/caregiver stimulation (e.g., programs that train parents how to provide a more supportive environment for their children). Evidence from a number of studies suggests that educational readiness at the time of entry into the formal school system (at age 5 or 6) is an important indicator of how well children will ultimately perform in school (Heckman et al., 2010; Schweinhart, 2007). Despite the importance of this stage of a child's development, the literature in China is almost completely silent about the early childhood development program experience in rural areas. In fact, because more than two-thirds of Chinese children still live in rural areas (or migrant communities), improving early childhood development programs in these areas should be a high priority for China's educators. There is a small set of recent studies from China that have shown how both nutrition interventions (Li et al., 2017; Luo et al., 2015) and programs that train parents to invest more in their children in terms of positive interactions (e.g., reading to their children more, interactively playing with them) can reduce the level of developmental delays when children are still young (Sylvia et al., 2018). If there are certain types of families that are susceptible to having children who suffer from developmental delays, the government could provide nutrition and parental training programs when their children are still in the 0–3 (or 0–6) age range.

The research of Heckman and Mosso (2014) and Heckman's book, *Giving Kids a Fair Chance* (Heckman, 2013) makes a case that programs for state-run or state-supported early childhood development are worth the investment. Raising the level of cognition and other noncognitive skills of children when they are very young has been shown repeatedly to raise the educational performance of the children when they enter school. The government of China, however, has invested little in initiatives focused on raising parental and caregiver attention to rural infants and toddlers and needs to develop and implement a nationwide early childhood care and development program that addresses the needs of vulnerable rural subpopulations. Notably, governments in middle-income countries, such as Brazil, Ecuador, Nicaragua, and Peru, are now committing large amounts of fiscal and human resources to such programs (Macours, Schady, & Vakis, 2008; Paxson & Schady, 2007; Schady, 2000; Schady & Paxson, 2007).

As noted, cognitive development is highly correlated with the educational performance of rural students and has implications for those who are cognitively slow and enrolled in a competitive schooling system. If a student falls behind his or her cohort, it is difficult to catch up. In the recent past, China eliminated fast and slow tracking in rural schools (Chen, Liu, Zhang, Shi, & Rozelle, 2010). Although there were good reasons for this, in light of this study's findings, we believe that a large proportion of rural students need to receive additional assistance in school so they have help when they are beginning to fall behind. There are many ways to do this besides returning to a fast/slow tracking system. Educators need to identify ways to help these children.

Despite these important findings, this study has several limitations. First, we do not test the causal relationship between cognitive development and educational performance. In the absence of long-term cohort studies that contain an experimental component, causality is not easy to identify. It could be that other factors that are correlated with IQ (for example, non-cognitive abilities), account for part of the strong correlation between IQ and school performance. Despite this possibility, in this case, correlation-based results suggest that there is a problem and that it is feasible to identify students who will be at risk of falling behind in school. Therefore, although we should be careful in interpreting the exact magnitude of the relationship between IQ and educational performance, we feel that we have shown that there is good reason to believe that this relationship exists and that IQ is an important determinant of learning in school. We understand, however, that our study does not address all of the issues involving early childhood development that may be helpful in explaining the education performance of rural students. For example, increasing attention has begun to be paid to the role of personality traits and noncognitive skills and their impact on student outcomes (Glewwe, Huang, & Park, 2017; Heaven & Ciarrochi, 2012; Leeson, Ciarrochi, & Heaven, 2008), which warrant further research.

Acknowledgments

This work was supported by the National Natural Science Foundation of China [Grant numbers 71603261, 71673008 and 71742002]; the Ministry of Education of Humanities and Social Science Project [Grant number 16YJC880107]; and the Chinese Universities Scientific Fund [Grant numbers 2018QC066 and 2018JG001].

Appendix A. Appendix

Table A1
Multivariate analysis of the differences for the correlates of iq scores and standardized math scores among subgroups.

Variable	Migrants vs. CLPs	Migrants vs. LBCs	CLPs vs. LBCs
IQ score	0.035***	0.034***	0.035***
	(0.001)	(0.001)	(0.001)
Group	-0.626*	-0.272	0.020
	(0.334)	(0.349)	(0.116)
Cross-term	-0.006***	-0.006***	0.000
	(0.001)	(0.001)	(0.001)
Gender dummy	0.013	0.040**	0.018
	(0.017)	(0.018)	(0.021)
Preschool	0.190***	0.199***	0.200***
	(0.031)	(0.031)	(0.043)
Number of siblings	-0.072***	-0.088***	-0.063***
	(0.014)	(0.015)	(0.016)
Father's age	0.921*	2.700***	-0.001
	(0.547)	(0.798)	(0.087)
Mother's age	-0.275	-1.890***	-0.193
	(0.426)	(0.639)	(0.215)

(*continued on next page*)

Table A1 (*continued*)

Variable	Migrants vs. CLPs	Migrants vs. LBCs	CLPs vs. LBCs
Father's education	0.006*	0.011***	0.007
	(0.003)	(0.004)	(0.004)
Mother's education	0.010***	0.008***	0.004
	(0.003)	(0.003)	(0.003)
Household assets	0.013*	0.014*	0.011
	(0.007)	(0.007)	(0.009)
Father smokes	-0.057***	-0.071***	-0.064***
	(0.019)	(0.019)	(0.022)
Father drinks	-0.030	-0.025	-0.051**
	(0.019)	(0.020)	(0.024)
School effects	yes	yes	yes
Constant	-27.460***	-35.250***	3.781
	(6.582)	(7.625)	(5.183)
Observations	8,451	8,279	6,390
R^2	0.360	0.370	0.427

Data Source: Author's survey.

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a For definition of Variables see Table 2.

b Groups in column (1) denote Migrants (=1) and CLPs (=0); Groups in column (2) denote Migrants (=1) and LBCs (=0); Groups in column (3) denote LBCs (=1) and CLPs (=0).

c Cross terms mean that the IQ scores multiply the groups.

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