Cognitive Skills, Non-Cognitive Skills, and the Employment and Wages of Young Adults in Rural China

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Abstract

The objective of this paper is to examine whether noncognitive skills explain differences in employment status and hourly wages even after controlling for age, experience, schooling and cognitive skills. Of particular interest is to examine the relative magnitudes of the impacts of the cognitive and noncognitive skills on these labor market outcomes. Data used in this paper come from the Gansu Survey of Children and Families (GSCF), which followed a random sample of 2,000 children in rural areas of Gansu Province who were 9-12 years old in the year 2000. Three waves of surveys were completed in 2000, 2004, and 2007-2009. The GSCF is the first large-scale data collection on child and adolescent cognitive and noncognitive skills in rural China.

I. Introduction

Economists have analyzed the impact of formal education, often measured in terms of years of schooling, on wages and other labor market outcomes ever since the seminal studies of Becker (1964) and Mincer (1974). In these studies, years of schooling are viewed as an investment in human capital that provides the student a return in the form of higher earnings during his or her working years. Many careful studies by economists have attempted to estimate the causal impact of years of schooling on wages; Card (1999, 2001) provides a thorough review of these efforts, focusing on developed countries.

Yet subsequent research has shown that the value of years of schooling can vary across schools and across students within the same school. This suggests that children's time in school does not by itself make them more productive workers. Instead, time in school is valuable only to the extent that it leads to the development of skills that have returns in the labor market (see Hanushek, 2002, for a discussion of supportive evidence from developed countries). This is especially true in developing countries, where studies have shown that mathematics, science and literacy skills vary widely across (and within) countries for children who have had the same years of schooling (see Hanushek and Woessman, 2008, for a recent review).

Until recently, the skills that economists have focused on are those that are generally classified as *cognitive* skills. The definition of this term varies, and some studies do not define it at all, but a good starting point is the American Psychological Association's (2007) definition of cognition: "all forms of knowing and awareness, such as perceiving, conceiving, remembering, reasoning, judging, imagining and problem solving." A simpler definition of cognitive skills is the knowledge that one has learned, and one's ability to learn new knowledge. Both economists and psychologists have long known that cognitive skills – or to use a somewhat different term, cognitive ability – have strong predictive power for economic and social outcomes. The predictive power of these skills fits easily into the human capital model developed by Becker, Mincer, and others; many, if not most, cognitive skills are developed when one is enrolled in school.

While there is a growing literature on the contribution of cognitive skills to earnings, there is a much smaller literature on the role of noncognitive skills, especially in developing countries. The objective of this paper is to examine whether noncognitive skills explain differences in employment status and hourly wages even after controlling for age, experience, schooling and cognitive skills. Of particular interest is to examine the relative magnitudes of the impacts of the cognitive and noncognitive skills on these labor market outcomes. To our knowledge, this paper is the first to examine the contribution of noncognitive skills to labor market outcomes in a developing country.

II. Data

This paper analyzes data collected in Gansu Province, which is located in northwest China and is one of that nation's poorest provinces, consistently ranked last or second to last in rural income per capita among Chinese provinces. In 2000, Gansu had a population of 25.6 million, 76 percent of whom resided in rural areas. Gansu's socioeconomic and educational profiles resemble those of other interior provinces in China. Relative to China as a whole, Gansu has low per capita income, high rates of illiteracy, and low per-child educational expenditures. Rural residents are predominantly employed in subsistence farming, animal husbandry, and migrant wage labor. The following subsections describe the data in more detail.

A. The Gansu Survey of Families and Children. The analysis in this paper is based on panel data from the Gansu Survey of Children and Families (GSCF), which followed a random sample of 2,000 children in rural areas of Gansu Province who were 9-12 years old in the year 2000. Three waves of surveys were completed in 2000, 2004, and 2007-2009. Among the children surveyed in 2000, only nine had never enrolled in school, and of the 1991 who had enrolled (all of whom did so before 2000) only 19 had left school before 2000. In each wave, the GSCF collected extensive data on these children using separate questionnaires administered to children, their parents, teachers, school principals, and community leaders.

One remarkable characteristic of the GSCF is its low rate of sample attrition. Of the 2,000 original children, all but one have complete information in the first wave of the survey, including a variety of tests and questions that measure both cognitive and non-cognitive skills. Of the 1,999 children with complete information in the first wave, 1,869 (93.5%) were re-interviewed in wave 2 (2004), when they were 13-17 years old.[1] Of these, all answered sets of questions designed to measure non-cognitive skills (i.e. completed the child questionnaire) and 1647 completed tests that measure cognitive skills.

Finally, wave 3 consists of two separate data collection efforts. First, household questionnaires were completed in the summer of 2007 by the children's parents, who provided information about children's enrolment history and current employment situation. Then, the children themselves were interviewed about 18 months later, during the 2009 spring festival (late January, 2009), when many who had migrated were likely to be visiting their families; if children were not at home but their parents were, then the parents were asked to answer some of the questions. The analysis in this paper uses the data from the child questionnaire that was

[1] In addition to the 1,869 children who were re-interviewed in wave 2, there are another 52 children from whom some information was collected from parents in the household questionnaire, although those children were not re-interviewed. Because we need information from the child questionnaire, these 52 are excluded from our analysis.

completed in early 2009, not the data from the household questionnaire completed in 2007. The wave 3 child questionnaire collected information from 1,858 of the original 2,000 children. (This includes 86 children for whom no data were collected in wave 2, so the 142 children with no data in wave 3 consist of 42 that were already missing in wave 2 and another 100 who were present in wave 2.) Of these 1,858 young people, 1407 (75.7%) completed the wave 3 tests for cognitive skills, 1421 (76.5%) completed wave 3 tests for non-cognitive skills, and 1413 (76.0%) have a complete set of both cognitive and non-cognitive skills for wave 3.

B. Data on Education, Cognitive Skills and Non-Cognitive Skills. The GSCF collected detailed data on the sample children's educational outcomes. The household questionnaires, completed in 2000, 2004, and 2007, included information on whether the child attended kindergarten (and, if so, how many years he or she attended), the age when the child first enrolled in primary school, whether any grades were repeated or skipped (and, if so, which ones), the most recent grade completed, current enrolment status, and the distance to the nearest primary, middle and high schools. Detailed data were also collected on parental expenditures on the child's education. Each of these variables was also collected for all of the child's siblings.

In the first two waves, additional data were obtained from the child's homeroom teacher, including that teacher's assessment of the child's behavior and study habits, as well as his or her past grades in Chinese and mathematics. While almost all children have grades for the school currently attended, only about half have grades for the school previously attended. Information was also solicited from the sample children's mothers about the child's behavior and attitudes towards schooling. Finally, a principal questionnaire provided more information about the school, and a village leader questionnaire collected information on the distances to the nearest schools.

A child questionnaire was completed in each survey wave. In the first two waves, in addition to asking questions about noncognitive skills (described below), children were asked questions about the time they spent on homework, as well as their attitudes toward education. In the third wave, the children were surveyed in early 2009 during spring festival (late January). As the children were older and most had completed schooling, the questions focused on school-to-work transitions, including detailed work histories, migration histories, and the earnings from and the characteristics of their current jobs.

The GSCF collected data on cognitive and non-cognitive skills in all three waves of the survey, although the specific skills covered vary by wave. These are summarized in Table 1. The following paragraphs describe each of the skill measurements in greater detail.

A general cognitive ability test was administered in the first wave of the GSCF. Developed by researchers at the Institute for Psychology of the Chinese Academy of Social Sciences, the test consists of four sets of questions. The first is a set of miscellaneous questions of common knowledge, such as “Who invented the light bulb?” The second set consists of somewhat abstract questions that ask what two objects have in common; an example of such a pair is “elbow” and “knee”. The third set asks children to solve simple arithmetic problems that are read out to them, and the fourth is a series of miscellaneous written arithmetic questions that must be answered within 30 to 75 seconds (example: “A child has 12 children’s books, he/she gives 5 of them to a friend. How many does he/she have left?”).

The Chinese and mathematics achievement tests collected in waves 1 and 2 were designed by experts at the Gansu Educational Bureau to cover the range of the official primary school curriculum. In 2004, separate exams were given to children in grades 1-2, 3-4, and 5-6 of primary school, and for each grade of middle school. The academic tests were administered in school classrooms for currently enrolled children, and in the village committee office for children who were no longer enrolled. In the first wave, half of the sample children were randomly assigned to take the Chinese test, while the other half took the mathematics test. In the second wave, all students took both tests. The wave 1, children were given 45 minutes to take the math test and 60 minutes to take the Chinese test. In wave 2, children in primary school were given 60 minutes to complete both tests (i.e. about 30 minutes each) and middle school students were given 90 minutes for both tests. Chinese and mathematics test were not administered in wave 3, since less than have of the sample were still in school in 2009, so there is no clear reference curriculum on which to base the tests.

Literacy ("life skills") tests were administered in waves 2 (2004) and 3 (2009). In waves 2 and 3 children were given 30 minutes to take this test. The tests are modeled after the International Adult Literacy Surveys (OECD and Statistics Canada, 2000) and were designed by an expert from the China Educational Research Institute in Beijing. They assess three domains of life skills: prose literacy, document literacy, and numeracy.

Prose literacy focuses on the knowledge and skills needed to understand and use information from texts that contain extended prose organized in a typical paragraph structure found in materials such as editorials, news stories, brochures and pamphlets, manuals, and fiction. Document literacy focuses on knowledge and skills required to locate and use information found in qualitatively different printed materials that contain more abbreviated language and use a variety of structural devices to convey meaning, such as tables, charts, graphs, indices, diagrams, maps, and schematics. Numeracy refers to the ability to interpret, apply, and communicate mathematical information in commonly encountered situations. Numeracy tasks can be characterized by the computational skills required and by the problem-solving strategies used. In contrast to the Chinese and math achievement tests administered in waves 1 and 2, the literacy test focuses on how to apply literacy and numeracy skills to function effectively in society. The same test was taken by everyone in the sample, regardless of their grade level. The wave 2 and 3 tests are not identical, since by 2009 these young adults should have developed more advanced skills. In particular, the wave 3 test included more questions on reading comprehension.

Measurements of non-cognitive skills are constructed from sets of questions included in the child questionnaires in each wave of the GSCF. Measures of internalizing behavior and externalizing behavior are asked in exactly the same way in waves 1 and 2. Internalizing behavior problems are *intra*personal in nature. The internalizing index captures the extent to which the child suffers from anxiety, depression and withdrawal. Externalizing problems are *inter*personal in nature and are characterized by destructive behavior, impulsivity, aggression and hyper-activity (Achenbach and Edelbrock, 1978; Hinshaw 1992; Dearing et al 2006). The child psychology literature suggests that environments that impede a child's self-regulatory efforts, as well as the presence of anti-social role models, increase the likelihood of a child developing externalizing problems (Evans, 2004). Environments that destabilize a child's sense of self control over his or her life may increase the likelihood of internalizing problems (Dearing et al 2006; Chorpita and Barlow, 1998).

To measure internalizing and externalizing behavior, each child was read 36 statements under the heading "Description of Your Life" and asked to indicate the extent to which they agreed with the statement, with four possible responses (fully agree, agree, disagree, totally disagree). Half of these statements were used to create an internalizing behavior index and the other half were used to create an externalizing behavior index. An example of a statement used for the internalizing index is: “I am shy.” An example of a statement used for the externalizing index is: “I often lose my temper with others.” From the two indices, normalized internalizing and externalizing variables were created; for both, a higher value indicates a child with more behavioral problems.

In wave 2, another set of questions, in the form of statements that respondents are then asked whether they agree, were used to measure children’s resilience. The series of statements is based on Song’s (2001, 2003) adaption of Noam and Goldstein’s (1998) “Resilience Inventory”. Resilience is defined as the capacity to achieve favorable outcomes despite challenges and “risk” factors. The Resilience Inventory (RI) was developed to be a culturally sensitive measure of child and adolescent resilience and has been administered to children and adolescents in the US, Thailand, China, Korea, Switzerland, and Israel. The GSCF adapted Song’s RI for Korea. Song (2001) generated six subscales of the RI for use on Korean adolescents. The subscales are: Optimism, Self-Efficacy, Relationships with Adults, Peer Relationships, Interpersonal Sensitivity and Emotional Control. This was the first large-scale data collection on child and adolescent “resilience” characteristics in rural China.

The third wave did not collect data on internalizing and externalizing behavior, nor on resilience, but it did administer two sets of questions to measure two other types of noncognitive skills, the Rosenberg Self-Esteem Scale assessment and the Center for Epidemiological Studies Depression Scale (CES-D). The main reason for using different tests is that the internalizing, externalizing and resilience tests are designed for children, while the self-esteem and depression test are designed for adults, and by wave 3 the children were 17-21 years old. The Rosenberg scale measures perceptions of self-worth. It is a 10-item scale, designed for adolescents and adults, that measures an individual's degree of approval or disapproval toward himself

(Rosenberg, 1965). The scale is short, widely used, and has accumulated evidence of validity and reliability. It contains 10 statements of self-approval and disapproval to which respondents are asked to strongly agree, agree, disagree, or strongly disagree.

CES-D is one of the most frequently used depression questionnaires that psychologists have constructed that can be used in general surveys to detect the presence of depressive symptoms. It was developed in the 1970s by Lenore Radloff (1977), while she was a researcher at the U.S. National Institute of Mental Health. It consists of 12 statements, such as "I felt that everything that I did was an effort". For a reference period of the past week, the respondent is asked to express the frequency of such feelings on a four point scale (No, Once in a while, Sometimes, and Frequently).

C. Employment and Wage Data. Of the 2,000 children sampled in the year 2000, information was collected for 1,858 of them using the child questionnaire that was administered in early 2009. Of these children, 846 (45.5%) were still in school, another 845 (45.5%) were working, and 167 (9.0%) are neither working nor in school. Note that some of this information was provided by the children's parents; of the 1,858 children, 423 were unavailable to directly answer the questionnaire because they had migrated and did not return home for the spring festival (240 children), were not at home for other reasons, such as military service or higher education (83 children), or for unknown reasons (100 children). Thus only 1,435 children were available to take tests of cognitive and non-cognitive skills in the 2009 data.

Of the 845 children who were working in 2009, 771 (91.2%) were working for wages and the rest were self-employed (or, in two cases, this information is missing). Among all 845 working children, 517 (61.2%) were working in another province, and 167 (19.8%) were working in Gansu province but in a different county than the one they grew up in.

The earnings regressions presented below use the log of the hourly wage as the dependent variable. It is computed based on the answers to three questions: monthly income from current job (including bonuses and subsidies), days worked per month, and hours worked per day. Of the 845 workers, 568 are classified as unskilled workers (manufacturing workers and restaurant workers are the most common categories) and the rest can be classified as skilled workers.

III. Estimation Strategy

The basic approach is to estimate standard models of these outcomes, and examine whether *non-cognitive* skills offer additional explanatory power for those labor market outcomes. Table 2 presents evidence that cognitive and non-cognitive skills measure different attributes. The general cognitive development test is moderately correlated with the Chinese and mathematics tests, with correlation coefficients of 0.322 and 0.247, respectively. (The correlation between the Chinese and mathematics tests cannot be calculated for 2000 since children took either one or the other.) In contrast the correlation between the Chinese and math test and the two tests of non-cognitive skills (internalizing and externalizing scales) is lower, ranging between -0.087 and -0.186 (one would expect negative correlation, since these non-cognitive skills have higher values of children with more behavioral problems). The cognitive development test is more correlated with non-cognitive skills (correlation coefficients of -0.246 and -0.298), but the strongest correlation of all is between the two non-cognitive skills (0.823).

Yet one needs to be very careful because the apparent impact of both cognitive and non-cognitive skills on labor market outcomes could reflect causal pathways in the opposite direction: an individual's employment status and wages could affect their current levels of both types of skills. Our main approach to address this problem is to use measures of both types of skills that were collected when the children were much younger: either the skills measured in 2000, when almost all of the sample children (98.6%) were in school, or the skills measured in 2004, when 89% of the sample children were still in school (and only 7% were working).

A second problem is omitted variable bias. In almost any regression estimate, some variables that have explanatory power are not available in the data set. If those variables, which in effect become part of the error term in the regression, are correlated with the explanatory variables in the regression the estimates of the causal impacts of the observed variables will be biased. For example, child "innate ability" could affect scores on test of cognitive skills but could also have direct effects on the decision to remain in school.

A third problem is bias due to measurement errors in the data, especially with respect to the scores on the cognitive and non-cognitive tests. It is well known that random errors in regressors generally lead to underestimation of the associated coefficients. Any variable that is measured by administering a test or a set of questions will have at least some measurement error in it, since respondents may make errors, and the test itself cannot fully capture the underlying concept. One way to remove, or at least minimize, this type of bias is to use instrumental variable methods, where the instrument is a "second measurement" of the underlying variable. For example, Chinese and math scores in 2000 could be used as IV's for the same variables in 2004, and vice versa.

A fourth problem, which applies only to estimates of the impact of cognitive and non-cognitive skills on wages, is selection bias. Only about 45% of the individuals in the sample were working for wages when they were interviewed in early 2009. These wage workers are unlikely to be a random sample of the original 2000 children, and the objective is to estimate a relationship that applies to the entire sample. To avoid sample selection bias we use the 2-step method first proposed by Heckman (1979). The first step consists of estimating a probit model of whether the individual works for wages in early 2009, and the second equation is the wage equation. There is little reason to think that the selection correction term is identified by arbitrary functional form assumptions about the error terms in these equations, so one or more variables is needed to that have predictive power for the probit regression but have no explanatory power for the earnings of wage earners. The main exclusion restriction used in this paper is whether the child passed the upper secondary school entrance examination; children who fail this exam cannot continue to upper secondary school, and this event is unlikely to have predictive power on wages after controlling for children's cognitive and non-cognitive skills.

Consider the roles of cognitive and non-cognitive skills in determining a child's current education/employment status. The sample children were 17-21 years old in 2009, and while many were still enrolled in school slightly more than half have finished their schooling. In terms of standard human capital theory, the children who have already left school have attained their optimal level of schooling, while those who are still in school have not yet reached their optimal level. Simple utility maximizing models (e.g. Glewwe, 2002) indicate that the following exogenous factors increase the number of years that children continue in school (and thus increase the probability that a young person is still in school in 2009): higher "learning efficiency", higher school quality, higher parental "tastes" for schooling, and a lower price of schooling (which could include lower travel costs). Learning efficiency can be divided further into parental education (better educated parents are more able to help their children with their schoolwork), households' purchases of educational services (e.g. tutoring services), children's "innate ability", and children's interest in schooling.

How do cognitive and non-cognitive skills fit in this simple model? First, the development of both types of skills could reflect different aspects of children's innate ability, and they could also reflect children's interest in (tastes for) schooling. Second, in the absence of precise measures of school quality, they could also reflect unobserved school quality (we will get around this by using commune or village fixed effects). Third, they could also reflect unobserved parental tastes for schooling, since parents who put more weight on their children's education presumably spend more time helping their children with their schoolwork (and give their children more encouragement to do well in school). Finally, to enter upper secondary school in China students must pass an academic entrance exam, and children's cognitive (and perhaps non-cognitive) skills almost certainly affect their performance on that exam. While there is growing literature on the contribution of cognitive skills to earnings, there is a much smaller literature on the role of non-cognitive skills, especially in developing countries. To our knowledge, this paper is the first to examine the contribution of non-cognitive skills to labor market outcome in a developing country.

Standard neoclassical models of the role of human capital in determining earnings assume that workers are paid the marginal product of their labor, and that higher levels of human capital increase those workers marginal product of labor and thus increase their wages. In theory, human capital can be treated as a set of many different types of skills, ranging from different types vocational training (some of which are primarily acquired through work experience) to higher order thinking skills. All of these can be thought of as cognitive skills. In addition, the productivity of most types of work depends on individuals' motivations and their ability to work well with others. These are their non-cognitive skills. In the wage regressions presented below, the first specifications include the standard factors that determine wages, namely work experience and years of education. These specifications are then expanded by adding measure of cognitive skills. Finally, then measures of non-cognitive skills are added. To avoid bias due to reverse causation (working conditions affect these skills), most specifications use measurements of these skills that were obtained before the vast majority of the sample children started working (e.g. measurements from waves 1 and 2).

IV. Results

This section presents estimates of the impact of cognitive and non-cognitive skills on the sample children's employment outcomes when they were 17-21 years old. The first subsection presents estimates of the impact on those skills on whether they are still in school, are working, or doing neither. The second subsection examines the impacts of those skills on their wages.

A. Determinants of Education and Employment Status. Table 3 presents multinomial logit estimates of the determinants of the sample children's education or employment status in 2009, when they were 17-21 years old. As explained above, data are available for 1858 of the original 2000 children, of which 846 (45.5%) are still in school, another 845 (45.5%) are working, and 167 (9.0%) are neither working nor in school. In all regressions the base group is students.

The first two columns of Table 3 present estimates that include only very basic explanatory variables, none of which measure either cognitive or non-cognitive skills. As expected, older students are more likely to be working or doing nothing, relative to being a student. Girls are no more likely to be in either category than boys. Children with educated parents, especially educated fathers, are less likely to be working or doing nothing; in other words, they were more likely to be in school, as one would expect. Children from better off families are also much less likely to be working than being a student, but this variable has no effect on the probability of doing nothing (relative to being a student). Several other variables that one may expect to be significant had no explanatory power and thus were dropped from the regression; these variables were distance to the nearest upper secondary school, number of bad harvests from 2000 to 2006, land holdings, child height-for-age Z-score, a dummy variable indicating a first-born child, and number of men and women of working age in the household in the year 2000.

The third and fourth columns of Table 3 add three cognitive skill variables that were measured in the year 2000, when the children were 9-12 years old and almost all of them (98.6%) were in school. These students were mainly in grades 3-6 at that time, and their scores on the mathematics and Chinese tests have strong negative predictive power on the likelihood that they were either working or doing nothing in 2009. The same result is also found for the cognitive development test given in the year 2000. Of course, this is not particularly surprising; even after controlling for parental education and wealth, there is additional variation in children's academic performance, and more generally in their cognitive development, and those who were learning skills more quickly are much more likely to remain in school.

The last two columns of Table 3 address the main question of this paper, whether *non-cognitive* skills have an impact on student's schooling to employment transitions over and above the predictive power of their cognitive skills. The two non-cognitive skills variables that were measured in the year 2000, when these children were 9-12 years old, are the internalizing and externalizing scales. The negative sign of the coefficients on the internalizing scale suggests that relatively withdrawn students are more likely to remain in school, although only the impact on doing nothing is statistically significant. The externalizing scale has significantly positive explanatory power for both the probability that children are working and the probability that children are doing nothing (relative to being in school). This suggests that children who were more aggressive, destructive and/or impulsive when they are 9-12 years old are less likely to be in school when they are 17-21 years old, even after accounting for their academic skills.

Inspection of the coefficient estimates in Table 3 suggests that they are similar for the two alternatives to remaining in school (working and doing nothing). Indeed, a chi-squared (joint) test of the equality of all the coefficients across these two alternatives cannot be rejected at the 5% level, although it is (just barely) rejected at the 10% level (p-value of 0.098). Thus the remainder of this subsection uses a simple logit, both to increase the efficiency of the estimates and also to allow for fixed effects estimation.

It is possible that unobserved community characteristics may be correlated with the explanatory variables in Table 3. For example, school quality could be highly correlated with children's acquisition of cognitive skills when they are 9-12 years old and it could have a direct effect on their education and employment decisions when they are 17-21 years old. Moreover, other community characteristics, such as local employment opportunities, may affect both non-cognitive skills at an early age (e.g. uncertain parental earnings could affect children's psycho-social development) and later education and employment decisions. It is very difficult to implement a multinomial logit model with fixed effects. Yet since the parameter estimates for working and doing nothing (relative to being in school) are very similar, one can group those two categories and estimate a simple logit model with village fixed effects. The results for these regressions are presented in Table 4.

The first three columns of results in Table 4 are similar to the three sets of results given in Table 3, and they confirm that grouping the working and doing nothing categories leads to very similar results. In particular, after controlling for age, sex, parental education, household income and distance to the nearest high school, students' cognitive skills (as measured by scores on the Chinese, mathematics and the general cognitive skills test) in 2000 have strong predictive power: higher scores increase the probability that they are still in school nine years later. Turning to non-cognitive skills, the externalizing score earlier in life greatly increases the probability that the child is not in school (most of these children are working) even after controlling for children's cognitive skills.

The marginal impacts of a one unit change in the variables are also given in column 3. Both cognitive and non-cognitive tests are standardized to have a standard deviation of one. The main result of interest here is that the impact of a one standard deviation change in the externalizing score is slightly larger than the impact of a one standard deviation change in the three cognitive skill variables. This demonstrates that the impact of this non-cognitive skill is not only statistically significant but also at least as large as the impacts of the cognitive skills.

Columns 4, 5 and 6 in Table 4 examine whether these results continue to hold when county fixed effects are added (recall that the 2000 children are located in 20 different counties). Very simply, the results continue to hold. Most importantly, a child who has a high externalizing score when he or she was age 9-12 is more likely not to be in school at age 17-21, even after conditioning on cognitive skills when the child was 9-12 years old. Indeed, when fixed effects are added the internalizing variable is weakly significant, so that children with higher internalizing scores are more likely to remain in school.

Table 5 presents the same estimates as Table 4, except that a linear probability model (OLS) specification is used instead of a binary logit specification. The results are very similar to those in Table 4, as is usually the case. Given this verification that the results are similar, the remaining results will use a linear probability model, which is more amenable for instrumental variable estimates.

As mentioned in Section IV, it is very likely that both the cognitive and non-cognitive skill variables, which are test scores, include random measurement error, which implies that they are likely to underestimate the true effects of these variables on the transition from education to employment. Fortunately, there are several instrumental variables for both types of skills, which can be used to minimize this bias. In particular, the mother questionnaire in wave 1 asks a large number of questions of the mother about the child's academic abilities. In addition, it asks the mother the exact same questions of the child that are used in the child questionnaire to construct the internalizing and externalizing variables. In addition, the child's homeroom teacher was asked to complete a questionnaire on the child's academic skills, as well as on the child's personality and behavior. These can be use as instruments for both the cognitive and non-cognitive skill variables. The results presented in columns 1-4 of Table 6 examine what happens to the results when the cognitive and non-cognitive skills variables are instrumented. The first two columns reproduce columns 3 and 6 of Table 5. The third column of Table 6 is the same specification as the second column (in particular, it has village fixed effects), except that it uses instrumental variables for the three cognitive skills variables and the two non-cognitive skills variables. As one would expect, the standard errors are much larger when instrumental variables are used; the main issue is whether the parameter estimates increase in absolute value, which is what one would expect if these variables have a large amount of random measurement error. There is almost no change in the effect of the Chinese score, although of course it is no longer statistically significant. On the other hand, the effect of the math score is about 60% larger (in absolute value), but again it is not significant because of the even larger increase in its standard error. In contrast, the effect of the general cognitive skills variable is almost four times as large, and is statistically significant at the 10% level.

Turning to the non-cognitive skill variables, the internalizing variable remains small and statistically insignificant, but the coefficient on the externalizing variable increases fourfold, although it loses significance. Given that the internalizing variable has no significant impact, and that it is relatively hard to find strong instruments for it, column 4 in Table 6 excludes that variable. The main effect of this change is to reduce the standard error on the externalizing variable to the point where it is highly significant, and still four times larger than the impact when instrumental variable estimation is not used. Overall, the instruments are not always "strong" enough to give precise results, but the estimates strongly suggest that there is measurement error in most, if not all of the cognitive and non-cognitive skill variables, and thus their impacts are, in general, underestimated in estimates that do not use instrumental variables.

The last two columns in Table 6 are the same as the first two columns except that they replace the 2000 Chinese, math, internalizing and externalizing variables with their 2004 counterparts. It also replaces the 2000 general cognitive skills test with the 2004 literacy (life skills) test. This was done in the hope that the 2004 scores may have less measurement error. Surprisingly, on four of the five tests the 2004 scores have lower explanatory power than the 2000 tests. The only exception is that the 2004 literacy (life skills) test has more explanatory power than the 2000 general cognitive skills test when village fixed effects are not used.

In 2004, an additional non-cognitive skill was measured: resilience. Interpreting its predictive power for staying in school is problematic because, as explained above, about 7% of children in 2004 had already left school, and most of them were working. Thus it is possible that their leaving school had an effect on their resilience as measured in 2004. Table 6B presents several regressions that investigate the impact of resilience on children's propensity to stay in school.

The first two columns in Table 6B simply add the resilience variable to the regressions in the first two columns of Table 6. Note that the sample size drops by about 90 students because these students did not take the resilience test in 2004. The main finding here is that, even after controlling for cognitive skills and externalizing and internalizing behavior, resilience has strong negative predictive power for working; that is, more resilient children are more likely to remain in school. The second column adds village fixed effects, and the result is the same. To avoid bias due to reverse causality, the third and fourth columns in Table 6B exclude the 183 children who were already working in 2004. There is very little change in the size of the impact of the resilience variable, and it is still highly significant. This 11% reduction in the sample size could also introduce selection bias, but the sample size reduction is not very large, and since less resilient children are more likely to drop out of the sample the main bias may be to underestimate the impact of resilience.

Recall that the resilience test can be decomposed into six different subscores, namely optimism, self-efficacy, relationships with adults, peer relationships, interpersonal sensitivity and emotional control. Columns 5 and 6 of Table 6B are the same as columns 1 and 2, except that the resilience variable has been replaced by these six subcomponents. Only one of the six components is significant at the 1% level in both columns 5 and 6: optimism. This indicates that children who were more optimistic at ages 13-16 are more likely to still be in school when they are 17-21 years old. One other component of the resilience index has predictive power, self-efficacy, but its significance is not as strong.

B. Determinants of Wages. As explained in Section IV, OLS estimates of earnings equations could suffer from sample selection bias. To avoid this bias a standard Heckman selection procedure is used. Table 7 presents two sets of probit estimates for whether an individual is working for a wage. For the first set, the binary dependent variables equals one for any person working for a wage, regardless of whether he or she has test score data collected in 2009 (wave 3). This is used for regressions that do not include wave 3 test scores, which are missing for over 400 individuals who have wage data in wave 3. For the second set, the binary dependent variable equals one for those who have wage data *and* have wave 3 test score variables.

The estimates in the first column of Table 7 are similar to those in the first column of Table 4, the main difference being that some additional variables were added to obtain identification of the wage equation from an exclusion restriction. The most important identifying variable is failing the high school entrance exam. This effectively bars students from continuing on to upper secondary school and so should have a strong positive predictive power for whether they are working. As long as students' cognitive and non-cognitive skills are included in the wage regressions, there is little reason to think that this variable also belongs in the wage regression, and hence it is a valid exclusion restriction. Two other variables that have predictive power and in principle do not belong in the wage regression are the parental education variables. Another variable with potential to be excluded from the wage regression that also has some explanatory power is the number of years for which the household experienced bad harvests from 2000 to 2006; households that experience more negative income shocks are likely to have difficulties financing their children's education and so their children are more likely to be working.[2] Two final variables that could have some explanatory power and that could be a valid exclusion restriction are the number of man and women of working age in the household in the year 2000. Households with more such men and women have less need of children, especially girls, to drop out of school in order to contribute to farm work and housework.

The results in the first column of Table 7 show that failing the upper secondary school entrance exam makes an individual much more likely to be working for a wage, as one would expect. A history of bad harvests from 2000 to 2006 significantly increases the probability that a child is working for a wage, which is also to be expected. Finally, the number of males of working age in the household in 2000 has no effect, but the number of women of working age has a negative effect, which suggests that girls face less pressure to leave school if there are other women in the household that can contribute to housework. The second probit estimate in Table 7 adds parental education as another variable that can predict children's working for a wage. As expected, both mother's and father's education have strong negative impacts.

Columns 3 and 4 in Table 7 repeat the estimates in columns 1 and 2, but the binary dependent variables equals one only if individuals work for a wage *and* have 2009 test score data. The results are broadly similar to those of the first two probits. They are shown here mainly for completeness, that is, to show that the probits that generate the selection correction term for the wage regressions that include the 2009 test scores also have identifying variables that have strong explanatory power.

Table 8 presents basic wage regressions, as well as regressions that use cognitive skill variables (but not non-cognitive skills variables) as regressors. Columns 1 and 2 use no cognitive skill variables at all; they are standard wage regressions in which wages depend on years of

[2] In the 2004 village leader questionnaire, those leaders were asked for reasons why children dropped out of lower secondary school; they could chose multiple reasons, and 51% cited that tuition and fees were too high, which was the second most cited reason.

schooling, years of experience, and job training, plus a dummy variable for women. In addition, two variables are added to control for employers who provide free meals (which reduce wages) and for jobs that necessitate that the employee rent housing to be close to the place of employment (which should increase wages). Finally, the inverse Mills ratio from the first probit regression in Table 7 is included. In column 1, it is based on the probit that does not use parents' education as an exclusion restriction (identifying variable for the selection correction term), while column 2 uses the probit that includes parents' education as an exclusion restriction.

The results in columns 1 and 2 of Table 8 are as one would expect. Young adults with more years of schooling receive higher wages, and the same is true of employees with more experience and with job-related training. The results are very similar when parents' education is excluded (column 1) or included (column 2) as an exclusion restriction in the probit equation. Another finding that is not surprising (for China) is that women's wages are about 25% lower than those of men. The dummy variables for employers that provide meals or employees that need to rent housing have the expected signs, but neither is statistically significant. Finally, the selection correction term is insignificant in both regressions.

If school quality varies substantially within Gansu province, the years of schooling variable does not fully capture the variation in skills that students obtain while in school. The remaining columns in Table 8 add cognitive skill variables to see whether they offer additional explanatory power. Column 3 uses the test scores that were administered in wave 1 (2000), while columns 4 and 5 do the same for waves 2 (2004) and 3 (2009), respectively. In all cases, none of these variables has any explanatory power, and the years of schooling variable maintains its statistical significance. None of the estimated parameters is very large, even allowing for some attenuation bias, and three of the seven have unexpected negative signs. This suggests that either there is little variation in school quality across Gansu province, so that years of schooling is a good indicator of skills learned in school, or the cognitive skill variables are measured with a large amount of error and thus their coefficients are biased toward zero. Of course, both could be true.

Finally, Table 9 presents results when variables are added that measure non-cognitive skills. In the first column, neither of the two non-cognitive skill variables that were measured in 2000 (internalizing and externalizing) is significant. This holds even if the three insignificant cognitive skill variables are removed from the regression (column 2). The same is true for three non-cognitive skills (internalizing, externalizing and resilience) measured in wave 2 (2004), as seen in column 3.

Yet the two non-cognitive skills measured in 2009, the Rosenberg self-esteem score and the CES-D depression variable do have statistically significant explanatory power for wages. In column 4, the Rosenberg scale has a significantly positive effect, as expected, and it is quite large: an increase of one standard deviation is associated with a 7% increase in wages. Similarly, in column 5 the depression index has a significantly negative impact, as one would expect. The impact is very large, in that an increase of one standard deviation leads to a 9% decrease in wages. Lastly, when both variables are measured together only the depression scale has a significant effect (their correlation coefficient is -0.294). Of course, it is possible that the results for 2009 are picking up reverse causality; getting a job with high wages may increase one's self-esteem, and getting that pays low wages may make one more depressed.

V. Summary

Our results indicate strong effects of non-cognitive skills on schooling years, but not labor productivity. It could be that the effects of non-cognitive skills are greater for those with more schooling years, in particular, children in our sample that have not yet entered the workforce (almost half of whom are in high school now). It could also be that the types of non-cognitive skills measured in our survey contribute more to the formation of cognitive skills and thus years of schooling. Thus a closer look at the formation of skills may give a more clear picture.

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Table 1: Cognitive and Non-Cognitive Skills in the Gansu Survey of Children and Families

Year	***Cognitive Skills***	***Non-Cognitive Skills***
2000	1. Chinese Test (half sample) 2. Math Test (other half) 3. General Cognitive Skills Test	1. Internalizing Behavior 2. Externalizing Behavior
2004	1. Achievement Tests 2. Literacy/Life Skills Test 3. Classroom grades	1. Internalizing Behavior 2. Externalizing Behavior 3. Resilience (with subscales in optimism, self-efficacy, adult relationship, peer relationship, interpersonal sensitivity and emotional control)
2008-09	1. Literacy/Life Skills Test (similar to one used in 2004)	1. Rosenberg Self-Esteem Scale 2. Depression Scale (from Center for Epidemiological Studies)

Table 2: Correlations Between Cognitive and Non-Cognitive Skills

Year 2000

	Chinese	Math	Cogn. Dev.	Internalizing	Externalizing
Chinese	1.0000				
Math	--	1.0000			
Cogn. Dev.	0.3223	0.2468	1.0000		
Internalizing	-0.1232	-0.0868	-0.2461	1.0000	
Externalizing	-0.1857	-0.1462	-0.2976	0.8234	1.0000

Table 3: Multinomial Logit: Factors that Influence Education/Employment in 2009, using 2000 Skills Data

	(1)		(2)		(3)	
Base group: Students			Add Cognitive		Add Cognitive and Non-Cognitive	
Outcome:	Working	Doing nothing	Working	Doing nothing	Working	Doing nothing
Chinese achievement test score in 2000			-0.246**	-0.297**	-0.238**	-0.296**
			(0.103)	(0.121)	(0.105)	(0.119)
Math achievement test score in 2000			-0.265***	-0.245	-0.257***	-0.243
			(0.0867)	(0.172)	(0.0858)	(0.169)
General cognitive skills test score in 2000			-0.208**	-0.252**	-0.165	-0.218**
			(0.104)	(0.101)	(0.103)	(0.107)
Internalizing scale in 2000					-0.116	-0.285**
					(0.0969)	(0.133)
Externalizing scale in 2000					0.272**	0.362**
					(0.108)	(0.153)
Age of sample children	0.474***	0.270***	0.539***	0.344***	0.557***	0.359***
	(0.0397)	(0.0635)	(0.0482)	(0.0524)	(0.0472)	(0.0600)
Gender dummy (=1 if female)	0.114	0.0388	0.106	0.0337	0.126	0.0515
	(0.168)	(0.271)	(0.166)	(0.278)	(0.165)	(0.279)
Father's years of schooling	-0.0933***	-0.0867***	-0.0867***	-0.0786***	-0.0869***	-0.0789***
	(0.0185)	(0.0285)	(0.0195)	(0.0289)	(0.0193)	(0.0286)
Mother's years of schooling	-0.0603***	-0.0487	-0.0446**	-0.0311	-0.0468**	-0.0341
	(0.0186)	(0.0299)	(0.0197)	(0.0335)	(0.0193)	(0.0338)
Log 2000 per capita wealth in 2009 Yuan	-0.303***	-0.0640	-0.252***	-0.00416	-0.246***	-0.00544
	(0.0742)	(0.143)	(0.0787)	(0.144)	(0.0822)	(0.147)
Constant	-5.915***	-5.468***	-7.697***	-7.541***	-8.091***	-7.828***
	(1.038)	(1.897)	(1.375)	(1.763)	(1.382)	(1.911)
Observations	1857		1857		1857	

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 4: Binary Logit: Factors that Influence Education/Employment in 2009, using 2000 Skills Data, Village Fixed Effects

Base group: Students	(1)	(2)	(3)		(4)	(5)	(6)
Outcome: Working or Doing nothing		Add Cognitive	Add Cognitive and Non-Cognitive	Marginal Effect		Add Cognitive	Add Cognitive and Non-Cognitive
Chinese achievement test score in 2000		-0.256***	-0.249***	-0.0523***		-0.212**	-0.200**
		(0.0925)	(0.0942)	(0.01941)		(0.0974)	(0.0957)
Math achievement test score in 2000		-0.262***	-0.255***	-.0536***		-0.301***	-0.293***
		(0.0873)	(0.0858)	(0.01765)		(0.0959)	(0.0928)
Literacy test score in 2000		-0.215**	-0.174*	-0.0366		-0.399***	-0.352***
		(0.0971)	(0.0967)	(0.0204)		(0.102)	(0.106)
Internalizing scale in 2000			-0.147	-0.0309			-0.144*
			(0.0948)	(0.0196)			(0.0856)
Externalizing scale in 2000			0.288***	0.0606***			0.328***
			(0.104)	(0.02123)			(0.100)
Age of sample children	0.437***	0.504***	0.521***	0.1096***	0.456***	0.570***	0.594***
	(0.0377)	(0.0407)	(0.0415)	(0.0084)	(0.0442)	(0.0538)	(0.0544)
Gender dummy =1 if female	0.100	0.0926	0.112	0.0236	0.0884	0.0720	0.0951
	(0.173)	(0.174)	(0.173)	(0.0362)	(0.176)	(0.173)	(0.172)
Years of schooling of Father	-0.0923***	-0.0854***	-0.0856***	-0.0180***	-0.0898***	-0.0836***	-0.0849***
	(0.0170)	(0.0184)	(0.0181)	(0.0037)	(0.0155)	(0.0165)	(0.0164)
Years of schooling of Mother	-0.0583***	-0.0424**	-0.0447***	-0.0094***	-0.0642***	-0.0519***	-0.0546***
	(0.0157)	(0.0176)	(0.0172)	(0.0035)	(0.0181)	(0.0190)	(0.0182)
Log of per capita wealth in 2000	-0.260***	-0.208**	-0.204**	-0.0428***	-0.234***	-0.188***	-0.187***
	(0.0781)	(0.0824)	(0.0857)	(0.01779)	(0.0660)	(0.0663)	(0.0671)
Constant	-5.346***	-7.180***	-7.553***				
	(1.103)	(1.331)	(1.363)				
Fixed effects at county level	**NO**	**NO**	**NO**		**YES**	**YES**	**YES**
Observations	1857	1857	1857		1857	1857	1857

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 5: Linear Probability Model: Factors that Influence Education/Employment in 2009, using 2000 Skills Data

Base group: Students	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Working or Doing nothing		Add Cognitive	Add Cognitive and Non-Cognitive		Add Cognitive	Add Cognitive and Non-Cognitive
Chinese achievement test score in 2000		-0.0581***	-0.0563**		-0.0446**	-0.0424**
		(0.0196)	(0.0197)		(0.0196)	(0.0190)
Math achievement test score in 2000		-0.0579***	-0.0564***		-0.0630***	-0.0610***
		(0.0188)	(0.0185)		(0.0191)	(0.0185)
General cognitive skills test score in 2000		-0.0427**	-0.0335		-0.0740***	-0.0637***
		(0.0203)	(0.0199)		(0.0196)	(0.0201)
Internalizing scale in 2000			-0.0310			-0.0280
			(0.0197)			(0.0170)
Externalizing scale in 2000			0.0610**			0.0653***
			(0.0216)			(0.0203)
Age of sample children	0.0906***	0.102***	0.104***	0.0908***	0.107***	0.111***
	(0.00702)	(0.00781)	(0.00792)	(0.00767)	(0.00847)	(0.00834)
Gender dummy =1 if female	0.0233	0.0212	0.0255	0.0192	0.0146	0.0195
	(0.0374)	(0.0366)	(0.0361)	(0.0363)	(0.0347)	(0.0342)
Father's years of schooling	-0.0180***	-0.0165***	-0.0165***	-0.0172***	-0.0158***	-0.0158***
	(0.00311)	(0.00326)	(0.00326)	(0.00277)	(0.00291)	(0.00289)
Mother's years of schooling	-0.0130***	-0.00943**	-0.00978***	-0.0135***	-0.0109***	-0.0113***
	(0.00314)	(0.00346)	(0.00333)	(0.00371)	(0.00379)	(0.00360)
Log 2000 per capita wealth in 2009 Yuan	-0.0558***	-0.0431**	-0.0418**	-0.0491***	-0.0373**	-0.0363**
	(0.0167)	(0.0172)	(0.0176)	(0.0137)	(0.0132)	(0.0132)
Constant	-0.595**	-0.940***	-1.006***	-0.654**	-1.093***	-1.165***
	(0.233)	(0.273)	(0.276)	(0.233)	(0.241)	(0.234)
Fixed effects at village level	**NO**	**NO**	**NO**	**YES**	**YES**	**YES**
Observations	1857	1857	1857	1857	1857	1857

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized.

Table 6: Linear Probability Model: Factors that Influence Education/Employment in 2009, using IV's and 2004 Skills Data

	(1)	(2)	(3)	(4)	(5)	(6)
Base group: Students			All children		2004 Scores	
Outcome: Working or Doing nothing			IV with internal	IV without internal		
Chinese achievement test score in 2000	-0.0563**	-0.0424**	-0.0481	-0.0511		
	(0.0197)	(0.0190)	(0.0932)	(0.0929)		
Math achievement test score in 2000	-0.0564***	-0.0610***	-0.0937	-0.0977		
	(0.0185)	(0.0185)	(0.138)	(0.136)		
General cognitive skills test score in 2000	-0.0335	-0.0637***	-0.224*	-0.222*		
	(0.0199)	(0.0201)	(0.121)	(0.120)		
Internalizing scale in 2000	-0.0310	-0.0280	0.0180			
	(0.0197)	(0.0170)	(0.175)			
Externalizing scale in 2000	0.0610**	0.0653***	0.233	0.247***		
	(0.0216)	(0.0203)	(0.174)	(0.0928)		
Chinese achievement test score in 2004					-0.0228	-0.0192
					(0.0174)	(0.0163)
Math achievement test score in 2004					-0.0358**	-0.0343**
					(0.0149)	(0.0146)
Literacy test score in 2004					-0.0726***	-0.0833***
					(0.0196)	(0.0193)
Internalizing scale in 2004					-0.0108	-0.0150
					(0.0184)	(0.0168)
Externalizing scale in 2004					0.00974	0.0153
					(0.0201)	(0.0191)
Age of sample children	0.104***	0.111***	0.163***	0.163***	0.0870***	0.0912***
	(0.00792)	(0.00834)	(0.0164)	(0.0164)	(0.00501)	(0.00611)
Gender dummy =1 if female	0.0255	0.0195	0.0293	0.0300	0.00152	-0.00373
	(0.0361)	(0.0342)	(0.0304)	(0.0298)	(0.0423)	(0.0397)
Years of schooling of Father	-0.0165***	-0.0158***	-0.0103***	-0.0104***	-0.0162***	-0.0160***
	(0.00326)	(0.00289)	(0.00321)	(0.00314)	(0.00290)	(0.00277)
Years of schooling of Mother	-0.00978***	-0.0113***	-0.00671	-0.00684	-0.00748	-0.00943*
	(0.00333)	(0.00360)	(0.00506)	(0.00478)	(0.00442)	(0.00503)
Log of per capita wealth in 2000	-0.0418**	-0.0363**	-0.00374	-0.00388	-0.0495***	-0.0366**
	(0.0176)	(0.0132)	(0.0156)	(0.0156)	(0.0162)	(0.0160)

	(1)	(2)	(3)	(4)	(5)	(6)
Dummy =1 if first born in HH			0.0177	0.0174		
			(0.0294)	(0.0289)		
Constant	-1.006***	-1.165***			-0.621***	-0.796***
	(0.276)	(0.234)			(0.205)	(0.225)
Fixed effects at village level	**NO**	**YES**	**YES**	**YES**	**NO**	**YES**
Observations	1857	1857	1782	1782	1557	1557

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 6B: Linear Probability Model: Factors that Influence Education/Employment in 2009, Adding 2004 Resilience Variable

Base group: Students Outcome: Working or Doing nothing	(1) All children	(2)	(3) Only children in school in 2004	(4)	(5) Resilience subscale	(6)
Chinese achievement test score in 2000	-0.0584***	-0.0458**	-0.0540**	-0.0402*	-0.0551**	-0.0423**
	(0.0200)	(0.0189)	(0.0212)	(0.0210)	(0.0201)	(0.0192)
Math achievement test score in 2000	-0.0556***	-0.0603***	-0.0551***	-0.0591***	-0.0549***	-0.0593***
	(0.0181)	(0.0183)	(0.0187)	(0.0185)	(0.0179)	(0.0182)
General cognitive skills test score in 2000	-0.0305	-0.0622***	-0.0268	-0.0561**	-0.0295	-0.0620***
	(0.0213)	(0.0213)	(0.0241)	(0.0236)	(0.0209)	(0.0216)
Internalizing scale in 2000	-0.0325	-0.0319*	-0.0338	-0.0354	-0.0340*	-0.0327*
	(0.0191)	(0.0169)	(0.0238)	(0.0208)	(0.0193)	(0.0167)
Externalizing scale in 2000	0.0564**	0.0644***	0.0585**	0.0698***	0.0583**	0.0659***
	(0.0219)	(0.0204)	(0.0242)	(0.0220)	(0.0210)	(0.0196)
Resilience scale in 2004	-0.0323***	-0.0325***	-0.0298**	-0.0324***		
	(0.0106)	(0.0112)	(0.0109)	(0.0113)		
Optimism scale in 2004					-0.0432***	-0.0390***
					(0.0123)	(0.0114)
Self-Efficacy scale in 2004					-0.0266*	-0.0337**
					(0.0132)	(0.0138)
Relationship with Adults scale in 2004					0.0169	0.0142
					(0.0145)	(0.0127)
Peer Relationship scale in 2004					-0.0109	-0.00653
					(0.0134)	(0.0142)
Interpersonal Sensitivity scale in 2004					0.0157	0.0158
					(0.0146)	(0.0143)
Emotional Control scale in 2004					0.00911	0.00989
					(0.0141)	(0.0147)
Age of sample children	0.0982***	0.107***	0.0804***	0.0898***	0.0981***	0.107***
	(0.00811)	(0.00879)	(0.00940)	(0.0109)	(0.00793)	(0.00850)
Gender dummy =1 if female	0.0333	0.0303	0.0339	0.0260	0.0305	0.0272
	(0.0352)	(0.0334)	(0.0380)	(0.0355)	(0.0338)	(0.0319)
Years of schooling of Father	-0.0182***	-0.0175***	-0.0170***	-0.0163***	-0.0180***	-0.0174***
	(0.00321)	(0.00282)	(0.00320)	(0.00293)	(0.00318)	(0.00275)

Years of schooling of Mother	-0.00929**	-0.0109***	-0.00849**	-0.0109**	-0.00893**	-0.0106***
	(0.00336)	(0.00346)	(0.00404)	(0.00408)	(0.00332)	(0.00344)
Log of per capita wealth in 2000	-0.0437**	-0.0365**	-0.0429**	-0.0338**	-0.0427**	-0.0361**
	(0.0176)	(0.0141)	(0.0180)	(0.0141)	(0.0180)	(0.0147)
Constant	-0.869***	-1.087***	-0.568*	-0.812**	-0.876***	-1.092***
	(0.280)	(0.249)	(0.295)	(0.299)	(0.278)	(0.244)
Fixed effects at village level	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Observations	1768	1768	1585	1585	1768	1768

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 7: Probit Estimates of Factors that Influence Education/Employment in 2009 (to generate selection correction terms)

	(1)	(2)	(3)	(4)
	Observe wage	Observe wage-with parent education	Observe wage and test scores	Observe wage and test scores-with parent educ.
Age of sample children	0.258***	0.262***	0.177***	0.178***
	(0.0339)	(0.0348)	(0.0372)	(0.0373)
Gender dummy =1 if female	0.0210	0.0250	-0.0510	-0.0468
	(0.0804)	(0.0820)	(0.0764)	(0.0775)
Years of schooling of Father		-0.0391***		-0.0352***
		(0.0108)		(0.00833)
Years of schooling of Mother		-0.0405***		-0.0210*
		(0.0144)		(0.0123)
Failed the entrance exam to high school	0.832***	0.843***	0.577***	0.577***
	(0.131)	(0.125)	(0.114)	(0.111)
Number of males of working age in HH in 2000	0.00110	-0.0252	-0.00682	-0.0274
	(0.0862)	(0.0891)	(0.0996)	(0.101)
Number of females of working age in HH in 2000	-0.157**	-0.166***	-0.105*	-0.109*
	(0.0620)	(0.0576)	(0.0617)	(0.0619)
Log of per capita wealth in 2000 (in 2009 yuan)	-0.121***	-0.0762**	-0.0617	-0.0300
	(0.0390)	(0.0381)	(0.0409)	(0.0406)
Years of bad harvest during 2000-2006	0.0646***	0.0625***	0.0553**	0.0548**
	(0.0206)	(0.0213)	(0.0229)	(0.0224)
Constant	-4.190***	-4.161***	-3.323***	-3.257***
	(0.645)	(0.648)	(0.750)	(0.764)
Observations	1860	1858	1860	1858

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 8: Wage Regressions for 2009 – The Role of Cognitive Skills

	(1)	(2)	(3)	(4)	(5)
Dependent variable: lnwage			2000 Cognitive Scores	2004 Cognitive Scores	2009 Cognitive
Years of schooling	0.0335**	0.0370***	0.0288*	0.0423***	0.0344*
	(0.0126)	(0.0117)	(0.0138)	(0.0144)	(0.0198)
Work experience measured in years	0.0334**	0.0364***	0.0306**	0.0248*	0.0280*
	(0.0117)	(0.0114)	(0.0114)	(0.0141)	(0.0146)
Had job-related training	0.237***	0.238***	0.236***	0.215***	0.241***
	(0.0460)	(0.0470)	(0.0465)	(0.0625)	(0.0616)
Chinese achievement test score in 2000			0.0174		
			(0.0440)		
Math achievement test score in 2000			-0.00530		
			(0.0276)		
Chinese achievement test score in 2004				0.0179	
				(0.0295)	
Math achievement test score in 2004				-0.0418	
				(0.0322)	
General cognitive development test score in 2000			0.0208		
			(0.0228)		
Literacy test score in 2004				-0.0211	
				(0.0327)	
Literacy test score in 2009					0.00991
					(0.0390)
Gender dummy =1 if female	-0.258***	-0.255***	-0.258***	-0.258***	-0.386***
	(0.0565)	(0.0569)	(0.0575)	(0.0639)	(0.0701)
Dummy =1 if employer provides free meals	-0.0121	-0.0147	-0.00979	-0.0578	-0.0260
	(0.0374)	(0.0372)	(0.0380)	(0.0435)	(0.0597)
Dummy =1 if need to spend money on rent for the job	0.00953	0.0134	0.0106	0.00177	-0.0182
	(0.0354)	(0.0349)	(0.0356)	(0.0396)	(0.0492)
Inverse Mills ratio for wage selection probit	-0.127		-0.125	-0.0973	
	(0.0753)		(0.0749)	(0.0792)	
Inverse Mills ratio, with parent education in probit		-0.0576			
		(0.0616)			
Inverse Mills ratio for test scores & wage selection probit					-0.0448

					(0.117)
Constant	1.182***	1.090***	1.228***	1.111***	1.238***
	(0.160)	(0.137)	(0.167)	(0.177)	(0.283)
Number of observations	809	807	809	651	506

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Internalizing scale, Externalizing scale are standardized

Table 9: Wage Regressions for 2009 – The Role of Non-Cognitive Skills

Dependent variable: lnwage	(1) 2000 scores	(2) 2000 Noncognitive only	(3) 2004 scores	(4) 2009 Rosenberg only	(5) 2009 CES-D only	(6) 2009 Rosenberg and CES-D
Years of schooling	0.0292*	0.0341**	0.0427***	0.0276	0.0287	0.0255
	(0.0140)	(0.0129)	(0.0138)	(0.0203)	(0.0205)	(0.0204)
Work experience measured in years	0.0312**	0.0340**	0.0224	0.0248	0.0249*	0.0229
	(0.0117)	(0.0119)	(0.0141)	(0.0161)	(0.0141)	(0.0151)
Had job-related training	0.234***	0.236***	0.207***	0.240***	0.233***	0.235***
	(0.0474)	(0.0468)	(0.0640)	(0.0595)	(0.0634)	(0.0619)
Chinese achievement test score in 2000	0.0179					
	(0.0436)					
Math achievement test score in 2000	-0.00443					
	(0.0275)					
Chinese achievement test score in 2004			0.0177			
			(0.0292)			
Math achievement test score in 2004			-0.0402			
			(0.0313)			
General cognitive development test score in 2000	0.0233					
	(0.0212)					
Literacy test score in 2004			-0.0185			
			(0.0306)			
Literacy test score in 2009				0.000528	0.00483	-0.000244
				(0.0360)	(0.0384)	(0.0360)
Internalizing scale in 2000	-0.00687	-0.00640				
	(0.0372)	(0.0377)				
Externalizing scale in 2000	0.0158	0.0107				
	(0.0282)	(0.0295)				
Internalizing scale in 2004			0.0495			
			(0.0334)			
Externalizing scale in 2004			-0.0133			

			(0.0336)			
Resilience scale in 2004			-0.00924			
			(0.0307)			
Standardized Rosenberg Self-Esteem Scale 2009				0.0742**		0.0497
				(0.0299)		(0.0332)
Percentiles of CES-D Depression Scale in 2009					-0.0942***	-0.0784**
					(0.0284)	(0.0321)
Gender dummy =1 if female	-0.256***	-0.258***	-0.260***	-0.386***	-0.385***	-0.387***
	(0.0570)	(0.0564)	(0.0641)	(0.0715)	(0.0716)	(0.0722)
Dummy =1 if employer provides free meals	-0.00995	-0.0122	-0.0568	-0.0343	-0.0377	-0.0416
	(0.0382)	(0.0378)	(0.0425)	(0.0597)	(0.0637)	(0.0624)
Dummy =1 if need to spend money on rent for the job	0.00982	0.00912	-0.00126	-0.0218	-0.00920	-0.0142
	(0.0357)	(0.0355)	(0.0384)	(0.0517)	(0.0487)	(0.0501)
Inverse Mills Ratio for Wage Selection Probit	-0.130	-0.130	-0.105			
	(0.0758)	(0.0764)	(0.0835)			
Inverse Mills Ratio for Rosenberg & Wage Selection Probit				-0.0441	-0.0266	-0.0246
				(0.123)	(0.111)	(0.117)
Constant	1.226***	1.178***	1.121***	1.317***	1.281***	1.319***
	(0.168)	(0.161)	(0.174)	(0.295)	(0.280)	(0.286)
Observations	809	809	650	498	503	498

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Scores on Chinese and Math achievement tests, Literacy test, Internalizing, Externalizing, Rosenberg, CES-D are standardized

Higher percentiles of CES-D means more depressed.