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Labor Market Outcomes, Cognitive Skills, and Noncognitive Skills in Rural China

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Abstract

A growing literature studies how cognitive and noncognitive skills influence labor market outcomes. This paper examines the relationship between childhood cognitive and noncognitive skills and labor market outcomes, using a rich longitudinal data set from rural China to overcome simultaneity concerns. We find that childhood cognitive skills have strong explanatory power for the wages of adults in their late 20s, even after controlling for years of education. We also find gender differences in the returns to various noncognitive skills, including internalizing and externalizing behavior.

Keywords: Cognitive skills, noncognitive skills, labor market returns, China, gender differences.

JEL Codes: I25, J16, J24, O53.

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1 Introduction

Economists are increasingly interested in the role of cognitive and noncognitive skills in determining individual labor market outcomes. A growing literature has studied how cognitive skills - and noncognitive skills such as personality traits, locus of control, motivation, and social skills - explain labor market outcomes.[1] Noncognitive skills provide a reconciling explanation for why some early childhood programs may have fading effects on test scores but re-emerging effects on wages later in life (Heckman et al., 2013). Compared to cognitive skills, which usually stabilize after the age of 10 (Almlund et al., 2011), noncognitive skills are also more malleable over the life cycle, providing a promising avenue for addressing persistent disadvantages. One strand of the literature shows the labor market could reward the same set of skills differently by gender and this could contribute to the gender wage gap (Mueller and Plug, 2006; Manning and Swaffield, 2008; Nyhus and Pons, 2005; Semykina and Linz, 2007). Most of the studies in the broader literature focus on developed countries, whereas such research in developing countries is very limited.

We use longitudinal data on rural children in northwestern China, the Gansu Survey of Children and Families (GSCF), to study how childhood cognitive and noncognitive skills predict the labor market outcomes of young adults in their mid to late 20s. Our basic approach is to estimate the standard models for these outcomes, including measures of cognitive and noncognitive skills. Unlike structural approaches, which typically combine multiple measurements into one latent skill measure, we include them separately to allow for the possibility that different skills, in particular different noncognitive skills, may have heterogeneous impacts. Our data have two advantages to mitigate potential endogeneity concerns, which is a common problem in this literature. First, we can control for many variables, including parental education, family wealth, and unobserved village characteristics in the basic specification to rule out any bias induced by these confounding factors. Second, since our skill measures are not contemporaneous with the outcomes, the reverse causality concern

[1] An incomplete list of this literature include Bowles et al. (2001); Heckman et al. (2006); Segal (2012); Heckman and Kautz (2012); Deming (2017).

that plagues many prior studies is largely alleviated. A further advantage of our data is that the rich information it contains enables us to explore additional outcomes, including fertility, occupational choices, and migration decisions.

Our results show that childhood cognitive skills consistently predict higher wages. A one standard deviation increase in the general cognitive skills measured at the age of 9 to 12 predicts 11.6% higher wages, and a one standard deviation increase in the literacy skills measured at the age of 13 to 16 predicts 10.2% higher wages.[2] These effect sizes decrease somewhat, to 7.5% and 6.8%, after controlling for years of schooling but are still statistically significant. Results also remain similar when controlling for occupation and migration further. While noncognitive skills do not seem to predict wages on average, we find intriguing gender differences in returns to noncognitive skills. Males with higher levels of internalizing behavior, measured around age 13 to 16, have lower wages, while female wages do not seem to be affected by this noncognitive skill. This suggests that males with tendencies to be withdrawn, against the social expectation of masculinity and boldness, are penalized by the labor market. Externalizing behavior at the same age also has predictions for wages that differ by gender: positive for males and negative for females. This finding is consistent with Mueller and Plug (2006), who show that agreeableness is positively correlated with wages for females but negatively for males using the Wisconsin Longitudinal Study. Overall, these results on gender differences suggest that diverging from social stereotypes may be penalized in the labor market.

This paper contributes to the literature on the returns to cognitive and noncognitive skills. Various studies have documented the impact of noncognitive skills on individuals' labor market outcomes (Bowles et al., 2001; Segal, 2012; Heckman and Kautz, 2012; Deming, 2017) and financial decisions and outcomes (Parise and Peijnenburg, 2019; Kuhnen and Melzer, 2018; Gong and Zhu, 2019; Cronqvist et al., 2016). However, almost all of these studies are based on data from developed countries. Evidence on returns to cognitive and noncognitive skills in developing countries is limited (Díaz et al., 2012; Glewwe et al., 2017; Hilger et al., 2018), largely due to data limitations. Because the industrial compositions of, and the skills needed

[2] We provide more details on the difference between these two measures in Section 2.

from, the labor force are quite different in developing countries relative to developed countries, it is important to have a better understanding in the developing country context. We find strong support for labor market returns to cognitive skills, even after controlling for years of education, but the average effects of noncognitive skills are often statistically insignificant. Our results differ from earlier work by Glewwe et al. (2017), who used waves 1 through 3 of the GSCF to study the school to work transitions and labor market returns to cognitive and noncognitive skills. They find no statistically significant relationship between cognitive (and noncognitive) skills and wages at age 19-21, after controlling for years of education. This paper takes advantage of the newly available wave 4 data, collected when the sample youths were in their mid- to late-20s. We explore several explanations for the differences between our results and those in that paper.

This study also contributes to a growing body of research on how noncognitive skills can be rewarded differently by gender and play a role in explaining the gender wage gap (Bertrand, 2011; Blau and Kahn, 2017). Prior studies decompose the gender wage gap by distinguishing contributions from gender differences in noncognitive skills, especially personality traits, and those from gender differences in returns to noncognitive skills. In particular, Mueller and Plug (2006) shows that 7.3% of the gender wage gap can be explained by differences in the Big Five Personality Traits and 4.5% can be explained by differences in returns to those personality traits. Similar findings are observed in the UK (Manning and Swaffield, 2008), the Netherlands (Nyhus and Pons, 2005), and Russia (Semykina and Linz, 2007). Most of these studies are based on data from developed countries, with the exception of Nordman et al. (2019), who study the decomposition of the gender wage gap using employer-employee survey data from Bangladesh. Our results on differing returns to internalizing and externalizing behavior by gender echo those of Manning and Swaffield (2008), who show that being disagreeable is rewarded for males but penalized for females. We also show that internalizing behavior is penalized for males but not for females.

The remainder of this paper is organized as follows. Section 2 provides more information on the data used, section 3 presents the empirical strategy, and section

4 reports the results. Section 5 concludes.

2 Data

We use data from the Gansu Survey of Children and Families (GSCF), which tracks individuals in rural Gansu from 9-12 years old through their mid- to late-20s between 2000 and 2015. Gansu is one of the poorest provinces in China. Compared with other provinces in China, it has lower average years of schooling and a larger proportion of the population in rural areas.

The GSCF has collected four waves of data, in 2000, 2004, 2007-2009, and 2015. The first two waves collected similar data on both cognitive and noncognitive skills when the sample individuals were 9 to 12 years old (wave 1) and 13 to 16 years old (wave 2). The first wave, in the year 2000, surveyed a representative sample of 2,000 children in 20 rural counties in Gansu, as well as their mothers, household heads, teachers, school principals, and village leaders. All but one of these 2,000 individuals have complete information in the first wave. The second wave, implemented in 2004, re-visited these individuals at age 13-16; 93.6% of the original sample, or 1,872 individuals, were re-interviewed in the second wave, and 1,773 completed achievement tests administered in their schools. The third wave, completed in early 2009, re-interviewed these individuals in their early adulthood. Of the original 2000 sample individuals, 1,437 (72%) were interviewed directly and completed skill tests in the third wave. Information was collected for an additional 426 sample individuals by surveying their parents.

The fourth wave in 2015 re-interviewed the sample individuals, who were then adults between 24-27 years old, and by which time most had entered the labor market. The wave 4 GSCF data include detailed job and income information for each respondent. Due to difficulties tracking the original 2,000 respondents given the information available at the time, the GSCF lost 631 (31.6%) of these respondents, partly due to other individuals with identical names living in the same village. Among the 1,369 individuals in the wave 4 final sample, 67% were interviewed face to face, 27% were interviewed on the phone and information on the remaining 6%

was collected via interviews with their parents.[3] We control for the type of interview in our analyses to account for potential reporting biases across these three interview methods.

2.1 Cognitive Skills and Noncognitive Skills

Longitudinal data on early life cognitive and noncognitive skills are rare for developing countries. The GSCF measured a rich set of cognitive skills and noncognitive skills in multiple waves. Cognition is defined as "all forms of knowing and awareness, such as perceiving, conceiving, remembering, reasoning, judging, imagining, and problem-solving." Measurements of cognitive skills in the GSCF include standardized reading and math scores in waves 1 and 2, a general cognitive ability test in wave 1, and literacy tests in waves 2 and 3. The reading and math achievement tests in waves 1 and 2 were designed by experts at the Gansu Educational Bureau to cover the official primary school curriculum. They varied by grade levels and were administered in school classrooms for currently enrolled children, and in village committee offices for out-of-school children. In wave 1, half of the sample individuals were randomly assigned to take the Chinese test and the other half took the math test. In wave 2, all students took both tests. Chinese and math tests were not administered in wave 3; less than half of the sample was still in school in 2009, so there was no common curriculum on which to base those tests.

The general cognitive ability test administered in wave 1 was developed by experts at the Institute for Psychology of the Chinese Academy of Social Sciences. It is comprised of four sets of questions, including common knowledge, abstract questions, orally administered arithmetic questions, and written arithmetic questions.[4] The literacy test conducted in waves 2 and 3 was designed to capture literacy and

[3] The GSCF also collected some information from their families for individuals interviewed on the phone.

[4] The first set of questions is miscellaneous questions of common knowledge. For example, "What does the stomach do?" The second set contains abstract questions that ask what two objects have in common, for example, elbow and knee. The third is a set of arithmetic problems that are read out to the children. The fourth set consists of written arithmetic questions to be answered within 30 to 75 seconds. For example, "A child has 12 children's books, he/she gives 5 of them to a friend. How many does he/she have left?".

numeracy skills more relevant for work and life activities, modeled after the International Adult Literacy Surveys (OECD, 2000).[5] In this paper, we focus on the standardized reading and math achievement scores in waves 1 and 2, the general cognitive ability test scores in wave 1, and the literacy test scores in wave 2. We do not include the literacy score in wave 3 since many individuals were already working by wave 3, which could cause endogeneity concerns. In addition, the literacy test in wave 3 had more missing data due to individuals who started working by then not being at home to take the test.

Noncognitive skills are patterns of thoughts, feelings, and behavior that affect social interactions with others. Measurements of noncognitive skills in the GSCF include internalizing behavior, externalizing behavior, and educational aspirations in waves 1 and 2. Internalizing behavior problems are intrapersonal, such as anxiety, depression, and withdrawal. Externalizing behavior problems are interpersonal, characterized by destructive behavior, impulsivity, aggression, and hyperactivity (Achenbach and Edelbrock, 1978). Child psychology research suggests that internalizing behavior problems tend to increase in environments that destabilize a child's sense of control over his or her life (Chorpita and Barlow, 1998; Dearing et al., 2006), while environments that impede a child's self-regulatory efforts, or the presence of antisocial role models, can increase externalizing problems (Evans, 2004). The GSCF used a set of survey questions to elicit the internalizing and externalizing behaviors often studied in the child psychology literature.[6] Educational aspirations are measured by their self-reported aspiration of college attendance or above. The GSCF did not measure internalizing and externalizing behavior in wave 3 since the survey instruments that measure them are designed for children and not appropriate for

[5]The literacy test assesses three literacy domains: prose literacy, document literacy, and numeracy. Prose literacy consists of knowledge and skills needed to understand and use information from texts containing extended prose organized in a paragraph structure that is typical of editorials, news stories, brochures, pamphlets, manuals, and fiction. Document literacy focuses on knowledge and skills for locating and using information found in printed materials that contain more abbreviated language and use a variety of devices to convey meaning, such as tables, charts, graphs, indices, diagrams, maps, and schematics. Numeracy is the ability to interpret, apply, and communicate mathematical information in commonly encountered situations.

[6]Detailed questions are listed in Table A1.

adults.[7]

2.2 Labor Market Outcomes

Our main outcome of interest is the logged hourly wage. Among the 1,322 individuals who reported labor force participation information, 1,155 (87%) reported that they were in the labor force. The labor force participation rate is 93% for males and 80% for females. The strongest predictor for labor force (non)participation is women with children. In the free-response section, many women who dropped out of the labor force specifically explain that they did so to take care of their child. Among those men and women who are in the labor force, 1,061 (92%) were currently working. To capture as much wage information as possible, we utilize additional information that the GSCF collected on each participant's most recent job. We update wage information for those who reported that their most recent job ended in the past three years, which allows us to add 102 observations for wages, in addition to 911 observations on current wages.[8] Overall, among the 1,369 wave 4 survey participants in the final sample, we observe the current or a recent wage for 1,013 (74%) of them.

Rural residents in Gansu usually have worked as either salaried employees, self-employed/small business owners, or farmers. The majority of those currently working (82%) were salaried employees. This group also has a higher average income than the other groups. Salaried employees reported their monthly salary, as well as daily working hours and weekly working days. We calculate their hourly wage by dividing their annual salary (monthly salary times twelve) by their annual working hours (daily hours times weekly days times 52 weeks).[9] Non-wage workers, such as farmers and self-employed small business owners, reported their annual income, as well as

[7] In waves 3 and 4, the GSCF measured self-esteem using the Rosenberg Self-Esteem Scale and Center for Epidemiological Studies Depression Scale, and administered the Big Five personality test in wave 4. Since our main outcomes of interest, years of schooling and wages, are observed in wave 4, we do not study the relationship between wages and these contemporaneously measured skills.

[8] There are a small proportion of observations who report they were currently working but their wage information is missing. Results are similar when we restrict our sample to current wages only and are available upon request.

[9] We also constructed a different hourly wage by accounting for annual bonuses in their annual income. Results using that wage variable are very similar.

months worked per year, days worked per month, and hours worked per day. We calculate their annual working hours by multiplying the three working time variables, and then we divide their annual income by this variable to obtain an hourly wage.

2.3 Summary Statistics

Table 1 presents summary statistics for the final sample. Slightly less than half (44.4%) of the individuals are female. On average, they attain 11.46 years of schooling, which is close to finishing secondary school. More than 40 percent of our sample had an educational attainment of lower secondary school or below, one in four finished upper secondary school (grade 12), and one in three had attended a vocational college or academic university. By 2015, 35.2% of them had migrated to economically advanced, coastal provinces. Slightly more than half (54.6%) were married, and 39.4% had at least one child. Wage or recent wage information was missing for 24% or 311 individuals, of which 180 are not in the labor force and the other 131 reported that they were working but did not report their income. For those who reported an annual income, the average annual income was 38,538 yuan, equivalent to around 5,500 USD. They worked for 2,764 hours per year on average, which is much higher than the average annual working hours in OECD countries. For example, the annual working hours in the United States was 1,783 in 2015.[10] The average hourly wage is 15.4 yuan (around 2.2 USD). Their parents are poorly educated, with average years of schooling for their fathers and mothers being 6.5 years and 3.9 years, respectively.

All measures of cognitive and noncognitive skills are standardized, separately for each wave, so they have a mean of zero and a standard deviation of one. Table A2 presents correlations between cognitive skills and noncognitive skills. The autocorrelations of cognitive skills are relatively high, ranging from 0.32 to 0.42. The lowest correlation is the one between cognitive skills measured in 2000 and those measured in 2009, which has the longest time period between measurements. The autocorrelations between noncognitive skills are lower, with 0.04 for internalizing behavior, 0.11 for externalizing behavior, and 0.15 for educational aspirations from

[10]See `https://stats.oecd.org/Index.aspx?DataSetCode=ANHRS.`, retrieved on 8/22/2020, OECD database.

wave 1 and wave 2. In terms of the cross-type correlations, there are relatively high correlations between cognitive skills and noncognitive skills measured in 2000, with internalizing and externalizing behavior negatively correlated with cognitive skills and educational aspiration positively correlated with cognitive skills. The cross-type correlations between noncognitive skills measured in 2004 and cognitive skills are quite low, perhaps due to increased volatility in noncognitive skills and personalities during puberty ages. Overall, the correlations in the data are broadly similar to those found in prior studies with different contexts.[11]

Table 2 presents the summary statistics by gender. Females have lower cognitive skills than males by 0.13 standard deviations in 2000. This gap increases to 0.26 standard deviations in 2004, measured by literacy skills, a measure very similar to cognitive skills. By 2009, the gap in literacy skills disappears, conditional on the sample with non-missing 2009 literacy data. Females had lower educational aspirations in 2000 and fewer externalizing behavioral problems during puberty ages in 2004. Females in the sample also have 15% lower log wealth per capita measured in the baseline.[12]

Looking at the outcomes, males attain 0.47 more years of education than females on average. Females are 5.6 percentage points less likely to have migrated to a more developed province, 16.8 percentage points more likely to have married, and 18.4 percentage points more likely to have had a child by their mid- to late-20s. In terms of labor market outcomes, females, unsurprisingly, are less likely to be in the labor force. Females' average annual income is more than a quarter lower than that of males. Although they work fewer hours, their hourly wage is still significantly lower than males' hourly wages. In particular, the average female hourly wage is 13 yuan, around 25% lower than the average male hourly wage of 17 yuan.

[11] The working paper version of Heckman et al. (2006) reports correlations between noncognitive skills and various cognitive skills, ranging between 0.07 and 0.21 for men, and between 0.21 and 0.33 for women. Lindqvist et al. (2011) report that the raw correlation coefficient between cognitive and noncognitive skills is 0.11 using a sample of Swedish military enlisted men.

[12] Rural households are allowed to have a second child when the first child is a girl, therefore females are in larger households (by 0.22). Even when looking at wealth instead of wealth per capita, females still were in families with a lower wealth measure in 2000, by around 10%, which could potentially be due to sex-selective abortions by wealthier families.

3 Empirical Strategies

3.1 Basic Model

How strongly do cognitive and noncognitive skills predict years of schooling and labor market outcomes of individuals in their late 20s? We largely follow Glewwe et al. (2017) in our estimation strategies. More specifically, we estimate the following regression:

$$\begin{aligned} y_{ivt} &= \beta_0 + \mathbf{X_{ivt}}\beta_1 + \beta_3 Cog_{ivt-1} + \beta_4 NCog_{ivt-1} \\ &\quad + \sigma_{\mathbf{v}} + \epsilon_{ivt} \end{aligned} \tag{1}$$

where y_{ivt} is the outcome of interest, including years of schooling and logged hourly wage, of individual i in year t who was raised in village v. Cognitive and noncognitive skills, measured in one or more previous waves to avoid bias due to reverse causality and denoted by Cog_{ivt-1} and $NCog_{ivt-1}$, are used as our explanatory variables. Finally, control variables, denoted by X_{ivt}, include gender, father?s and mother's years of education, childhood household per capita wealth, interview types, age, and village fixed effects (denoted by σ_v). As mentioned earlier, for standardized math and Chinese scores in wave 1, half of the sample was randomly selected to take the math test and the other half took the Chinese test. We assign zero to the missing values and include a dummy variable for whether the individual took the math or the Chinese test in wave 1.

Researchers face several empirical challenges when estimating labor market returns to cognitive and noncognitive skills. First, studies using contemporaneous noncognitive measures to explain labor market outcomes cannot fully address bias due to reverse causality.[13] Although many studies impose the assumption that noncognitive skills and personality stay constant after an early age, the evidence is not conclusive on the stability of these skills. While Cobb-Clark and Schurer

[13]Some studies use contemporaneous measures regressing the noncognitive measures against a set of polynomials of age to control for how they change with age; they then use the predicted residuals in the regressions for labor market outcomes. However, this does not completely eliminate bias from labor market influences on noncognitive skills (Nyhus and Pons, 2012).

(2012) find that the Big Five personality traits stay relatively constant within a four-year period using panel data from Australia, Almlund et al. (2011) state that the preponderance of the evidence supports the view that personality traits are not set in stone. For example, Srivastava et al. (2003) show that conscientiousness and agreeableness increase with age among women. In our specification, we focus on the cognitive and noncognitive skills measured in waves 1 and 2 to avoid bias due to reverse causality.

Second, quantifying cognitive skills and noncognitive skills using tests and survey questions is plagued with measurement error problems, which could lead to biased (often attenuated) estimates. In this paper, we use the Item Response Theory (IRT) to construct the noncognitive skill variables (Das and Zajonc, 2010; Jacob and Rothstein, 2016). More specifically, we use a graded response model since the survey questions are ordered categories on a scale. This method is a generalization of the two-parameter logistic IRT model, in which we use the item difficulty and the item discrimination as parameters to fit the model. This method is widely used in the psychology literature to construct skill variables.

Third, cognitive and noncognitive skills are often correlated with one another. Noncognitive skills could affect the acquisition of cognitive skills and thus could affect individuals' performance on tests of cognitive ability (Segal, 2012, 2013; Cunha and Heckman, 2008). We follow Lindqvist et al. (2011) and provide estimation bounds on the potential biases from noncognitive skills and cognitive skills influencing each other's measures. We estimate the effects of cognitive and noncognitive skills by themselves and the effects of both. Taken together, these two sets of estimates can provide upper and lower bounds for the impact of each type of skills.

Lastly, since wages are not observed for everyone due to labor force non-participation or non-reporting of wages among the employed, we face the classic selection bias problem. In addition, as explained above the GSCF survey, as with many other longitudinal surveys, has sizeable sample attrition. We account for both selection problems by adding two predicted probability terms (inverse Mill's ratios) using Heckman selection models. To correct for the sample attrition, we use 1% micro data of the 2005 Mini-Census to calculate the popularity of last names at the county level (the sample includes individuals from 20 different counties). For individuals with last names that do not exist in the 1% Mini-Census, we assign their last name popularity to be zero and add an indicator variable to identify these individuals with no match in the 1% census. We use the first and second polynomials of the last name popularity (proportion of the people in the county with that last name), the no-match last name popularity dummy, as well as household size and household housing value in wave 1 as the identifying variables in the Heckman selection model. The first stage results are presented in Table A3. As expected, respondents with more popular last names are more likely to be missing in the final sample. Respondents in larger households and lower housing values are less likely to be missing, which could reflect the cost and financial constraint of household migration. Those with fewer family members and more valuable assets could more easily move away, making it more difficult to track them across waves. For the missing wage correction, we use marital status, having a child, and the interaction term between female and having a child as the exogenous variables in the Heckman selection model. Females with children are much more likely to drop out of the labor force. Table A3 shows that the predictive power of the variables excluded from the outcome regressions is strong for both selection correction probit regressions, with p-values of 0.03 for sample attrition and 0.00002 for missing wage.

4 Empirical Results

We first discuss how cognitive and noncognitive skills predict years of schooling and wages. We then look at additional outcomes, such as fertility, migration, and occupational choices.

4.1 Determinants of Years of schooling

Table 3 shows the OLS regression results on how cognitive and noncognitive skills predict years of schooling, accounting for sample attrition using the Heckman selection method. Column 1 uses cognitive and noncognitive skills in wave 1 (2000), and column 2 uses skill measurements in wave 2 (2004). The cognitive skill variables include standardized Chinese and math test scores in both 2000 and 2004, the standardized general cognitive ability test score in 2000, and the standardized literacy test score in 2004. Cognitive skills measured in both waves generally have positive impacts on individuals' years of schooling. A one standard deviation increase in the general cognitive score in wave 1 or the literacy score in wave 2 led to around 1.05 more years of schooling. For standardized Chinese and math scores in 2000, a one standard deviation increase in either score leads to around 0.4 more years of schooling. The effect sizes are smaller and statistically insignificant for standardized Chinese and math scores in 2004, although they are jointly significant with a p-value of 0.016.

Turning to noncognitive skills, individuals with more externalizing behavior achieved lower years of schooling. A one standard deviation increase in externalizing behavior measured in 2000 (2004) reduced years of education by 0.52 (0.35) years. Internalizing behavior has no significant effect on years of schooling. Education aspirations in 2004 predict higher years of schooling, while the coefficient of education aspirations in 2000 is also positive but statistically insignificant. Students may have a clearer understanding of their educational aspirations when they were 13-16 years old, when they were near the end of the nine-year compulsory schooling in China. Table A4 presents results when we include cognitive skills and noncognitive skills separately. Effect sizes are larger for both cognitive and noncognitive skills when we include only one set but not the other set.

These results are similar to the findings in Glewwe et al. (2017), who use an ordered probit model to account for censoring in data for those individuals who were still in school. Our measurement of years of schooling is from wave 4, when the sampled individuals were 24-27 years old and the vast majority had finished schooling and entered the labor market.[14] Hence, our estimation provides longer-run and more conclusive results on the impact of childhood skills on years of schooling.

[14]Sixty-four people reported that they are still in school.

4.2 Cognitive and Noncognitive Skills and Wages

Table 4 reports the effects of cognitive and noncognitive skills on wages after controlling for family background, unobserved village characteristics, and selection correction terms for sample attrition and missing wages. Across all columns, females earn 21.6% to 26.8% lower wages than males in our sample. Columns (1) and (2) show the impact of cognitive and noncognitive skills on wages without controlling for years of schooling and work experience. The effects of standardized general cognitive scores in 2000 and standardized literacy scores in 2004 are positive and statistically significant. An increase of one standard deviation in the cognitive score measured at age 9-12 leads to 11.6% higher wages by the mid to late 20s, and a one standard deviation increase in the literacy score measured at age 13-16 results in 10.2% higher wages by the mid to late 20s. Standardized Chinese and math scores do not seem to have strong predictive power on wages after controlling for general cognitive skills. None of the coefficients for noncognitive skills are statistically significant.

Columns (3) and (4) present the results including controls for years of schooling and work experience. Years of schooling and years of experience are both positively correlated with wages. Returns to childhood cognitive skills are still statistically significant, although the magnitudes are slightly smaller at 6.8% to 7.5%.[15] This is different from findings by Heckman et al. (2010) and Glewwe et al. (2017), who find no statistically significant relationship between wages and cognitive skills after controlling for educational attainment.

We explore several potential explanations for why our findings differ, in particular from Glewwe et al. (2017). First, cognitive and noncognitive skills may have a stronger effect on wages of college graduates, and the additional wave of data in sample respondents' mid-to-late 20s allows us to capture college graduates' wages in our sample. To test this possibility, we conduct subsample analysis using college graduates only but do not find any supporting evidence for this explanation. In an alternative specification, we include an interaction term between the college degree dummy and the cognitive skills and still do not find evidence supporting a larger

[15]When we include cognitive skills and noncognitive skills separately, effect sizes are similar as shown in Table A5.

return to cognitive skills for college graduates.

Second, it could be that the increase in the sample size of wage earners helps improve precision, since more sample individuals started working in wave 4. However, the point estimates of wage returns to cognitive skills measured in 2000 and 2004 in Glewwe et al. (2017) were 3% and -1.3%, which are much smaller than the point estimates from our results. We restrict our sample to those who started working in 2009, the same sample used by Glewwe et al. (2017), and regress their wages in 2009 and wages 2015 on childhood skills and control variables. We find results similar to those of Glewwe et al. (2017) on wages in 2009: cognitive skills do not statistically significantly predict wages in the early 20s for those individuals who left schools relatively early to work. When we look at the same individuals' wages in 2015, however, we find large effects of cognitive skills measured in 2000 on wages in 2015 even after controlling for years of schooling and experience, and smaller and statistically insignificant effect sizes for literacy skills measured in 2004.

These findings using those who were already working in their early 20s suggest two plausible explanations. First, it may take time for employers to observe cognitive skills that are not already reflected by years of schooling and then reward them with higher wages. Second, it may also take time for individuals to find jobs best suited for their abilities. We test between these two possibilities by looking at two subsamples among the early workers: those who stayed in the same occupation from 2009 to 2015 and those who did not. Note that the sample sizes are quite small when we split the samples this way, which limits the statistical significance of results. Results presented in Table A7 are inconclusive; the results for 2000, albeit imprecise, suggest that the returns to cognitive skills are higher for those who switched occupations, supporting the second hypothesis that cognitive skills are more valuable when the individuals find better matches in the job market, yet the (also imprecise) results for 2004 suggest higher returns for those who did not switch occupations.

4.3 Migration, Fertility, and Occupations

In addition to years of schooling and wages, cognitive and noncognitive skills could also influence migration, fertility, and occupational choices. First, migrant workers in the urban areas of developed provinces tend to make higher wages than those who stay in rural areas or less developed provinces. We generate a dummy variable indicating whether the individual migrated to an economically advanced city or province, instead of staying in Gansu Province or a nearby central or western province. Second, women with children are more likely to drop out of the labor force or to choose a job with more flexible hours but lower pay. We generate an indicator for whether the individual has at least one child. Finally, occupations with higher skill requirements often offer higher wages. We calculate the average wages for nine occupations and aggregate them into three groups. The highest group include professionals and finance, with an average hourly wage at around 19 yuan per hour; the second-highest group includes construction or mining, transportation, and public sector, with an average hourly wage between 15 to 16 yuan per hour; the rest of the occupations, including agriculture, manufacturing, sales, and services, are categorized the lowest paying group, with an average hourly wage between 13 to 14 yuan per hour.

Table 5 presents results from OLS regressions. Individuals with higher cognitive skills are more likely to migrate to an economically advanced province, less likely to have children, and more likely to work in a higher-paying occupation, all of which improve labor market outcomes. Similar to the results for wages, the predictive power of standardized Chinese and math scores is limited. The only significant result here is that standardized math test scores in 2000 predict a higher chance of entering higher-paying occupations. As for noncognitive skills, results are less clear and mostly statistically insignificant. Internalizing behavior measured in 2000 predicts a higher likelihood of migrating to an economically advanced province, but the internalizing behavior measured in 2004 is not statistically significantly correlated with this outcome. Externalizing behavior predicts a lower likelihood of entering a high-paying occupation. Education aspirations also seem to help delay the childbirth, especially education aspirations measured in lower secondary school. Finally, father's education predicts later childbirth and better occupational outcomes.

5 Gender Differences

To explore gender differences in the returns to cognitive and noncognitive skills, we add interaction terms between the female dummy variable and both cognitive and noncognitive skills to Equation 1. We find intriguing gender differences in the predictive power of noncognitive skills for wages.

Similar to the main results, we focus on gender differences in the impacts of cognitive and noncognitive skills on years of schooling and the log hourly wage. Because of long-standing son-preference in China, parents may be more likely to send boys with higher cognitive skills to upper secondary schools and colleges than to send girls with higher cognitive skills, resulting in a negative coefficient before the interaction term between female and cognitive skills. Alternatively, parents may send boys to upper secondary schools regardless of their cognitive skills and only invest in further schooling for girls with high cognitive skills, which would result in a positive coefficient before the interaction term between female and cognitive skills. Table 6 shows that the coefficients on the female dummy variable interacted with cognitive skill in 2000 or literacy skill in 2004 are positive but statistically insignificant; they are also small compared to the main effect of cognitive skills. The interaction term between female and 2004 internalizing behavior is the only one that is marginally statistically significant at the ten percent level. It suggests that males with higher internalizing behavior measured in 2004 achieve more years of schooling, while female educational attainment is insensitive to internalizing behavioral problems measured at the age of puberty.

In Table 7, we consider the gender difference in the impacts of cognitive and noncognitive skills on wages. Similar to Table 4, the first two columns present results without controlling for years of education and years of experience, while columns (3) and (4) control for them. We do not observe a significant gender difference in returns to cognitive skills. On the other hand, noncognitive skills measured in 2004 have strikingly different effects on wages for males versus females. First, a one standard deviation increase in internalizing behavior predicts an 8.7% reduction in wages for males, while its effect on females is positive (5.3%) but statistically insignificant. Since males are expected to be bold, their tendencies to withdraw could have a penalizing effect in the labor market settings. Second, a one standard deviation increase in externalizing behavior in 2004 predicts 6.7% higher wages for males, while it predicts 15.3% lower wages for females. Males are rewarded for their aggressive externalizing behavioral tendencies while females are punished.[16] This is perhaps the most striking contrast among the findings. The same skill has statistically significant predictive power on wages for females and males in the *opposite* direction. This finding echoes the results of Mueller and Plug (2006), who find that men earn a premium for being disagreeable, but not women. These gender differences highlight how social environments may reward certain noncognitive skills for one population when they are expected while penalizing the same skill for another population when they are not expected. Lastly, educational aspirations in wave 2 predict lower wages for males, while they are positive and statistically insignificant in predicting wages for females. The finding for males is perplexing and may be worth exploring in future research.

One interesting, and somewhat puzzling, finding is that the economic returns to internalizing and externalizing behavior measures during ages 9-12 versus results using measures from age 13-16 are very different. In particular, we do not find gender differences using the earlier measures, but significant gender differences using the latter measures. One potential explanation for why we do not see results using earlier measures is that the noncognitive measures in wave 2 during years of puberty are more closely correlated with adulthood noncognitive skills, which is supported by Table A8 showing that measures from age 13-16 overall have much stronger correlations with their big five personalities in the mid to late 20s.

[16] Results are similar after controlling for occupations and are available upon request.

6 Conclusions

A growing number of studies examine how cognitive and noncognitive skills influence labor market outcomes (Heckman et al., 2010; Lindqvist et al., 2011; Glewwe et al., 2017). This is one of the few studies studying returns to cognitive and noncognitive skills in a developing country context. We use the Gansu Survey of Children and Families, a rich longitudinal data set from rural China tracking children from 9-12 years old into their late 20s. Skills measured in individuals' childhood allow us to avoid the reverse causality concerns of studies that use skills measured contemporaneously with wages. Different from Heckman et al. (2010) and Glewwe et al. (2017), who find that the relationship between wage and cognitive skills disappears after controlling years of schooling, we find that general cognitive skills have explanatory power for wages after controlling for years of schooling. Although we find that better noncognitive skills play a role in increasing years of schooling, the impacts of noncognitive skills on wages are almost always statistically insignificant.

Despite a null effect of noncognitive skills on average, we find intriguing gender differences in returns to noncognitive skills, including internalizing behavior, externalizing behavior, and educational aspirations. Noncognitive skills measured in 2004 have strikingly different predictions on the wages of males and females. Internalizing behavior predicts a lower wage for males, while it does not have a strong predictive power for females. Externalizing behavior is rewarded for males and but penalized for females. These gender differences highlight how social environments may reward certain noncognitive skills for one population when they are expected while penalizing the same skill for another population when they are not expected.

Our results raise additional questions for which our sample is too small, or insufficient in other ways, to provide for conclusive answers. One question is why the relationship between cognitive skills and wages, even after conditioning on years of schooling, emerges only after some years in the labor market. Administrative income data linked with a longitudinal survey with a larger sample size could provide a more complete understanding of this relationship. Another question for future research is the interaction between social norms and returns to noncognitive skills, and how their interaction leads to gender differences in labor market outcomes. Finally, the predictive power of childhood skills, both cognitive and non-cognitive, on labor market outcomes suggests a need for additional research on the determinants of childhood cognitive and noncognitive skills.

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Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Mean	Standard Deviation	Min	Max	N
Female	0.444	0.497	0	1	1,369
Age in 2015	26.05	1.163	23	28	1,369
Father years of education	6.460	3.103	0	14	1,368
Mother years of education	3.919	3.137	0	11	1,369
Log wealth per capita in 2000	8.132	1.014	3.851	11.33	1,369
Years of schooling	11.46	3.473	0	18	1,369
Labor force participation	0.874	0.332	0	1	1,322
Employed	0.919	0.274	0	1	1,155
Annual income	38,977	23,935	1,700	310,000	1,013
Annual working hours	2,846	927.4	48	8,669	1,013
Hourly wage	15.63	16.72	1.042	400	1,013
Log hourly wage	2.549	0.592	0.0408	5.991	1,013
Migrate to economically advanced province	0.352	0.478	0	1	1,312
Married	0.546	0.498	0	1	1,329
Have a child	0.394	0.489	0	1	1,369
Missing wage	0.260	0.439	0	1	1,369

Data source: Gansu Survey of Children and Families.

Table 2: Summary Statistics: Gender Differences

	Male		Female - Male	
VARIABLES	Mean	Standard Deviation	Difference	Standard Error
Age in 2015	26.07	1.181	-0.035	(0.0633)
Father years of education	6.491	3.095	-0.071	(0.169)
Mother years of education	3.976	3.125	-0.129	(0.171)
Log wealth per capita in 2000	8.197	1.016	-0.146***	(0.0550)
Years of schooling	11.67	3.384	-0.474**	(0.189)
Labor force participation	0.928	0.258	-0.124***	(0.0181)
Employed	0.934	0.248	-0.039**	(0.0164)
Annual income	43,955	26,041	-12,093***	(1,481)
Annual working hours	2,914	938.3	-164.9***	(59.01)
Hourly wage	17.27	19.41	-4.003***	(1.060)
Log hourly wage	2.663	0.558	-0.275***	(0.0368)
Migrate to economically advanced province	0.377	0.485	-0.056**	(0.0266)
Married	0.472	0.500	0.168***	(0.0271)
Have a child	0.313	0.464	0.184***	(0.0261)
Missing wage	0.217	0.412	0.097***	(0.0237)
General cognitive 2000	0.039	0.971	-0.129**	(0.0532)
Literacy skill 2004	0.122	0.928	-0.261***	(0.0562)
Literacy skill 2009	0.016	1.015	-0.005	(0.0619)
Internalizing 2000	0.009	1.010	0.016	(0.0542)
Externalizing 2000	0.025	1.018	-0.001	(0.0540)
Education aspiration 2000	0.053	0.990	-0.149***	(0.0544)
Internalizing 2004	0.021	0.995	-0.063	(0.0554)
Externalizing 2004	0.093	1.000	-0.230***	(0.0546)
Education aspiration 2004	0.042	0.978	-0.065	(0.0547)

Data source: Gansu Survey of Children and Families.

Table 3: Effects of Cognitive and Noncognitive Skills on Educational Attainment

	(1)	(2)
Dependent Variable	Years of schooling	
Cog/Noncog skills measured in	2000	2004
Cognitive (2000) or literacy (2004)	1.047***	1.058***
	(0.169)	(0.120)
Standardized Chinese	0.372**	0.177*
	(0.142)	(0.106)
Standardized math	0.347**	0.198
	(0.132)	(0.136)
Internalizing	0.180	0.163
	(0.177)	(0.158)
Externalizing	-0.524***	-0.348**
	(0.197)	(0.147)
Education aspiration	0.144	0.459***
	(0.0900)	(0.111)
IMR for sample attrition	-0.735	1.896
	(2.129)	(2.025)
Female	-0.367	-0.326
	(0.233)	(0.230)
Father years of education	0.186***	0.143***
	(0.0369)	(0.0391)
Mother years of education	0.0929**	0.0991**
	(0.0424)	(0.0390)
Log wealth per capita in 2000	0.295**	0.330**
	(0.120)	(0.144)
Age in 2015	-0.527***	-0.207**
	(0.0954)	(0.0868)
Observations	1,310	1,174
R-squared	0.342	0.375
Village FE	Y	Y

Notes: This table reports OLS results including village fixed effects. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effects of Cognitive and Noncognitive Skills on Wage

	(1)	(2)	(3)	(4)
Dependant Variable	ln(wage) in 2015			
Cog/Noncog skills measured in	2000	2004	2000	2004
Control for Years of Education	No		Yes	
Cognitive (2000) or literacy (2004)	0.116***	0.102***	0.0753*	0.0679**
	(0.0382)	(0.0269)	(0.0412)	(0.0273)
Standardized Chinese	0.0406	0.0264	0.0365	0.0263
	(0.0322)	(0.0208)	(0.0337)	(0.0213)
Standardized math	-0.0315	-0.0150	-0.0397	-0.0122
	(0.0287)	(0.0251)	(0.0278)	(0.0243)
Internalizing	-0.0352	-0.00317	-0.0384	-0.0205
	(0.0343)	(0.0318)	(0.0339)	(0.0311)
Externalizing	0.0335	-0.0432	0.0471	-0.0273
	(0.0375)	(0.0364)	(0.0373)	(0.0350)
Education aspiration	-0.00864	-0.0221	-0.0103	-0.0370
	(0.0236)	(0.0247)	(0.0234)	(0.0245)
IMR for sample attrition	-0.281	0.0171	-0.144	0.0427
	(0.467)	(0.463)	(0.468)	(0.484)
IMR for missing wage	0.393**	0.400***	0.333*	0.277**
	(0.170)	(0.137)	(0.173)	(0.130)
Female	-0.216***	-0.248***	-0.230***	-0.268***
	(0.0620)	(0.0603)	(0.0614)	(0.0595)
Father years of education	0.00799	0.00760	0.00191	0.00385
	(0.00749)	(0.00814)	(0.00775)	(0.00824)
Mother years of education	-0.00397	-0.00387	-0.00365	-0.00339
	(0.00780)	(0.00735)	(0.00796)	(0.00718)
Log wealth per capita in 2000	-0.0175	-0.0249	-0.0224	-0.0347
	(0.0304)	(0.0320)	(0.0298)	(0.0311)
Telephone interview	0.0619	0.103**	0.0768*	0.105**
	(0.0436)	(0.0458)	(0.0439)	(0.0475)
Parent interview	-0.0562	-0.0548	-0.00875	-0.000899
	(0.0706)	(0.102)	(0.0814)	(0.107)
Years of schooling			0.0713***	0.0790***
			(0.0219)	(0.0209)
Years of experience			0.0450**	0.0543***
			(0.0199)	(0.0198)
Observations	961	865	961	865
R-squared	0.212	0.224	0.229	0.241
Village FE	Y	Y	Y	Y

Notes: This table reports OLS results including village fixed effects. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Relationship between Skills and Additional Outcomes: Migration, Fertility, Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Variable	Migrate to economically advanced province		Have child		High Paying Occupation	
Cog/Noncog Measured in	2000	2004	2000	2004	2000	2004
Cognitive (2000) or literacy (2004)	0.0432**	0.00780	-0.0291	-0.0528***	0.0886**	0.0760***
	(0.0196)	(0.0148)	(0.0213)	(0.0167)	(0.0364)	(0.0272)
Standardized Chinese	0.0316	0.0215	-0.0208	-0.0289	0.0713*	0.00421
	(0.0236)	(0.0190)	(0.0212)	(0.0188)	(0.0397)	(0.0284)
Standardized math	-0.00198	0.00207	-0.0436**	-0.0149	0.0714**	0.0206
	(0.0239)	(0.0198)	(0.0195)	(0.0160)	(0.0345)	(0.0351)
Internalizing	0.0548**	-0.00243	-0.0164	0.00765	0.0454	0.0120
	(0.0243)	(0.0223)	(0.0224)	(0.0213)	(0.0378)	(0.0343)
Externalizing	-0.0186	0.0138	0.0124	-0.0171	-0.0750*	-0.0264
	(0.0266)	(0.0247)	(0.0251)	(0.0228)	(0.0430)	(0.0366)
Education aspiration	-0.00750	-0.00617	-0.0206	-0.0265**	-0.00193	0.0138
	(0.0147)	(0.0152)	(0.0136)	(0.0131)	(0.0243)	(0.0209)
Female	-0.0487	-0.0554*	0.181***	0.177***	-0.155***	-0.143***
	(0.0319)	(0.0322)	(0.0256)	(0.0285)	(0.0492)	(0.0485)
Father years of education	0.00282	0.000671	-0.0185***	-0.0155***	0.0274***	0.0242***
	(0.00523)	(0.00572)	(0.00463)	(0.00474)	(0.00767)	(0.00790)
Mother years of education	-0.00755	-0.0111**	-0.00235	-0.000947	0.00764	0.00470
	(0.00537)	(0.00555)	(0.00513)	(0.00569)	(0.00871)	(0.00972)
Log wealth per capita in 2000	0.0231	0.0239	-0.00955	-0.00249	0.0301	0.0418
	(0.0182)	(0.0193)	(0.0156)	(0.0157)	(0.0243)	(0.0276)
Age in 2015	-0.0122	-0.00276	0.0970***	0.0864***	-0.0275	-0.00622
	(0.0133)	(0.0143)	(0.0134)	(0.0144)	(0.0220)	(0.0253)
Observations	1,310	1,180	1,367	1,227	1,174	1,060
R-squared	0.153	0.171	0.214	0.229	0.160	0.151
Village FE	Y	Y	Y	Y	Y	Y

Notes: This table reports OLS results including inverse mills ratios to correct for sample attrition and missing wage selection. Robust standard errors clustered at the village level in parentheses.

Table 6: Gender Difference: Cognitive and Noncognitive skills and Years of Schooling

	(1)	(2)
Dependant Variable	Years of schooling	
Cog/Noncog skills measured in	2000	2004
Cognitive (2000) or literacy (2004)	1.016***	1.005***
	(0.178)	(0.156)
Standardized Chinese	0.368**	0.175*
	(0.143)	(0.105)
Standardized math	0.345**	0.205
	(0.132)	(0.135)
Internalizing	0.149	0.436**
	(0.231)	(0.207)
Externalizing	-0.525**	-0.572***
	(0.239)	(0.189)
Education aspiration	0.0840	0.449***
	(0.115)	(0.143)
Female X cognitive	0.0665	0.0795
	(0.172)	(0.188)
Female X internalizing	0.0652	-0.570*
	(0.286)	(0.314)
Female X externalizing	0.00309	0.479
	(0.320)	(0.318)
Female X education aspiration	0.130	0.0400
	(0.184)	(0.209)
IMR for sample attrition	-0.717	1.743
	(2.122)	(2.024)
Female	-0.363	-0.319
	(0.232)	(0.229)
Father years of education	0.187***	0.146***
	(0.0371)	(0.0399)
Mother years of education	0.0932**	0.0987**
	(0.0426)	(0.0388)
Log wealth per capita in 2000	0.294**	0.329**
	(0.121)	(0.143)
Age in 2015	-0.525***	-0.210**
	(0.0955)	(0.0875)
Observations	1,310	1,174
R-squared	0.342	0.378

Notes: This table reports OLS results including village fixed effects. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Gender Difference: Relationship between Wage and Cog/Noncog Skills

	(1)	(2)	(3)	(4)
Dependant Variable		ln(wage) in 2015		
Cog/Noncog skills measured in	2000	2004	2000	2004
Control for Years of Education	No		Yes	
Cognitive (2000) or literacy (2004)	0.122***	0.117***	0.0771	0.0756**
	(0.0418)	(0.0364)	(0.0465)	(0.0374)
Standardized Chinese	0.0392	0.0243	0.0357	0.0231
	(0.0317)	(0.0211)	(0.0330)	(0.0215)
Standardized math	-0.0279	-0.0116	-0.0362	-0.00835
	(0.0291)	(0.0260)	(0.0282)	(0.0253)
Internalizing	-0.00483	-0.0600	-0.00794	-0.0872**
	(0.0463)	(0.0417)	(0.0472)	(0.0397)
Externalizing	0.0151	0.0423	0.0294	0.0672*
	(0.0506)	(0.0389)	(0.0521)	(0.0370)
Education aspiration	-0.0251	-0.0570*	-0.0245	-0.0767**
	(0.0319)	(0.0311)	(0.0313)	(0.0318)
Female X cognitive	-0.0143	-0.0339	-0.00622	-0.0129
	(0.0444)	(0.0496)	(0.0441)	(0.0526)
Female X internalizing	-0.0669	0.117*	-0.0676	0.139**
	(0.0877)	(0.0594)	(0.0894)	(0.0577)
Female X externalizing	0.0382	-0.198***	0.0376	-0.220***
	(0.0913)	(0.0561)	(0.0933)	(0.0545)
Female X education aspiration	0.0388	0.0884**	0.0330	0.0970**
	(0.0463)	(0.0445)	(0.0455)	(0.0476)
Female X years of schooling			-0.00189	-0.0218
			(0.0133)	(0.0146)
Years of schooling			0.0722***	0.0850***
			(0.0227)	(0.0209)
Years of experience			0.0454**	0.0511***
			(0.0200)	(0.0194)
Observations	961	865	961	865
R-squared	0.213	0.240	0.230	0.260
Village FE	Y	Y	Y	Y

Notes: This table reports OLS results controlling for interview type dummies, wave I household wealth, father education, mother education, the Inverse Mills Ratio for sample attrition correction and the Inverse Mills Ratio for missing wage correction. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix: Supplementary Figures and Tables

Table A1: Noncognitive Skills Measurement

Internalizing Behavior Questions	**Externalizing Behavior Questions**
I don't want others to meddle in my own business.	I break things on purpose.
I can't concentrate on what I am doing.	I lose my temper.
I have many strange / weird ideas (often daydream).	Even if I know I am wrong, I am reluctant to listen to others.
I easily get flushed. (I am easily frustrated or anxious).	I steal things from others or my home.
I can't do things well when my parents are not present.	I like to show off my strengths in front of others.
I am very indifferent to others.	I always want to be the center of attention.
I am very shy.	I quarrel with others.
I always want to be the center of attention.	I do not observe school discipline.
I am often teased by classmates.	I like to brag.
I do not feel guilty, even if I have done something wrong.	It bothers me if others do things better than I do.
My temper changes quickly and easily.	I act impulsively.
I feel inferior to others.	I often am suspicious of others.
I often am suspicious of others.	I often say obscenities.
I prefer to be alone.	I often make fun of others.
I often feel nervous.	I sometimes tell lies.
I am often bore.d	I am easily angered.
I stay quiet when I am with my classmates or friends.	I often disregard other people's ideas.
There is always something to worry about.	I sometimes menace and even hurt others.

Table A2: Correlations between Cognitive and Noncognitive Skills

	cognitive 2000	literacy 2004	literacy 2009	internalizing 2000	externalizing 2000	motivation 2000	internalizing 2004	externalizing 2004	motivation 2004
cognitive 2000	1								
literacy 2004	0.3805	1							
literacy 2009	0.3171	0.416	1						
internalizing 2000	-0.2743	-0.2518	-0.2436	1					
externalizing 2000	-0.29	-0.2746	-0.2332	0.8426	1				
motivation 2000	0.2115	0.1869	0.1046	-0.149	-0.1928	1			
internalizing 2004	0.0397	0.0481	-0.0212	0.0391	0.0321	-0.0387	1		
externalizing 2004	0.0092	-0.0348	-0.0841	0.0832	0.1104	-0.0646	0.7576	1	
motivation 2004	0.1591	0.2626	0.2525	-0.1144	-0.1358	0.155	-0.0714	-0.1251	1

Data source: Gansu Survey of Children and Families.

Table A3: First Stage of Heckman Selection

	(1)	(2)
VARIABLES	Final Sample	Missing Wage
County lastname popularity	2.487	
	(1.742)	
County lastname popularity squared	-18.98**	
	(9.291)	
Missing county lastname popularity	-0.0711	
	(0.102)	
Household size in 2000	0.0805**	
	(0.0351)	
Log housing value in 2000	0.0298	
	(0.0509)	
Log wealth per capita in 2000	0.0427	
	(0.0629)	
Mother years of education	0.00212	
	(0.00395)	
Female	-0.144**	-0.0167
	(0.0666)	(0.108)
Cognitive 2000	-0.0392	-0.142***
	(0.0342)	(0.0427)
Have child		-0.0234
		(0.144)
Female X have child		0.488***
		(0.160)
Married		0.119
		(0.117)
Internalizing 2000		-0.0437
		(0.0681)
Externalizing 2000		0.0670
		(0.0698)
Edu Aspiration 2000		-0.0168
		(0.0393)
Observations	1,745	1,328
Chi2 of the identifying variables	10.868	24.796
Prob> Chi2	0.0281	0.00002

Notes: This table presents the coefficients from Probit regressions in the first stage of the Heckman Selection Model. The identifying variables for sample attrition include last name popularity and squared, last name popularity no match dummy, household size, and household housing value in the baseline. The identifying variables for missing wages include female interacted with having children, having children, and marriage.

Table A4: Education Effect Bounds: Excluding Either Cognitive or Noncognitive skills

	(1)	(2)	(3)	(4)
Dependent Variable		Years of schooling		
Cog/Noncog skills measured in	2000	2004	2000	2004
Cognitive (2000) or literacy (2004)	1.197***	1.182***		
	(0.180)	(0.118)		
Standardized Chinese	0.406***	0.225**		
	(0.144)	(0.106)		
Standardized math	0.372***	0.241*		
	(0.135)	(0.135)		
Internalizing			0.111	0.201
			(0.179)	(0.156)
Externalizing			-0.715***	-0.436***
			(0.198)	(0.159)
Education aspiration			0.273***	0.800***
			(0.0960)	(0.103)
IMR for sample attrition	-0.969	1.934	3.321*	3.033
	(2.183)	(1.991)	(1.863)	(1.854)
Female	-0.361	-0.256	-0.664***	-0.696***
	(0.241)	(0.238)	(0.234)	(0.226)
Father years of education	0.193***	0.154***	0.198***	0.192***
	(0.0377)	(0.0391)	(0.0378)	(0.0389)
Mother years of education	0.0859**	0.0922**	0.128***	0.121***
	(0.0425)	(0.0405)	(0.0407)	(0.0377)
Log wealth per capita in 2000	0.321***	0.333**	0.409***	0.412***
	(0.120)	(0.137)	(0.121)	(0.137)
Age in 2015	-0.504***	-0.203**	-0.291***	-0.131*
	(0.0902)	(0.0873)	(0.0837)	(0.0747)
Observations	1,310	1,175	1,310	1,276
R-squared	0.330	0.356	0.286	0.304
Village FE	Y	Y	Y	Y

Notes: This table reports OLS results including the same controls as in Table 3. Robust standard errors clustered at the village level in parentheses.

Table A5: Wage Effect Bounds: Excluding either Noncognitive or Cognitive Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ln(wage) in 2015							
Cog/Noncog skills measured in	2000	2004	2000	2004	2000	2004	2000	2004
Control for Years of Education	No				Yes			
Cognitive (2000) or literacy (2004)	0.118***	0.0988***			0.0773*	0.0634**		
	(0.0371)	(0.0272)			(0.0409)	(0.0278)		
Standardized Chinese	0.0414	0.0275			0.0370	0.0260		
	(0.0322)	(0.0211)			(0.0338)	(0.0216)		
Standardized math	-0.0316	-0.0139			-0.0396	-0.0128		
	(0.0287)	(0.0251)			(0.0276)	(0.0245)		
Internalizing			-0.0589*	-0.00694			-0.0530	-0.0299
			(0.0341)	(0.0300)			(0.0333)	(0.0286)
Externalizing			0.0383	-0.0335			0.0533	-0.0136
			(0.0380)	(0.0341)			(0.0375)	(0.0320)
Education aspiration			-0.00584	-0.000301			-0.00978	-0.0246
			(0.0239)	(0.0228)			(0.0235)	(0.0227)
Years of schooling					0.0682***	0.0730***	0.0884***	0.102***
					(0.0214)	(0.0209)	(0.0195)	(0.0180)
Years of experience					0.0423**	0.0489**	0.0602***	0.0698***
					(0.0195)	(0.0196)	(0.0174)	(0.0167)
Observations	961	866	961	938	961	866	961	938
R-squared	0.210	0.217	0.195	0.195	0.227	0.234	0.220	0.227
Village FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports OLS results including the same controls as in Table 4. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Restricting Sample to Early Workers: Relationship between Wage and Cog/Noncog Skills

	(1)	(2)	(3)	(4)
VARIABLES	lnwage in 2009			
Cog/Noncog skills measured in	2000	2004	2000	2004
Control for Years of Education	No		Yes	
Cognitive (2000) or literacy (2004)	0.0434	-0.0219	-0.0199	-0.0488
	(0.0560)	(0.0419)	(0.0606)	(0.0439)
Standardized Chinese	0.0229	-0.0176	0.0144	-0.00460
	(0.0484)	(0.0457)	(0.0471)	(0.0441)
Standardized math	0.0435	-0.00981	0.0351	-0.00894
	(0.0521)	(0.0409)	(0.0524)	(0.0420)
Internalizing	-0.00566	0.0715	-0.0288	0.0657
	(0.0550)	(0.0517)	(0.0571)	(0.0502)
Externalizing	-0.00195	-0.0439	0.0328	-0.0329
	(0.0572)	(0.0562)	(0.0570)	(0.0553)
Education aspiration	-0.0420	-0.00291	-0.0429	-0.0102
	(0.0303)	(0.0330)	(0.0301)	(0.0332)
Years of schooling			0.103***	0.0771*
			(0.0350)	(0.0393)
Years of experience			0.0764**	0.0552
			(0.0344)	(0.0394)
Observations	560	476	560	476
R-squared	0.256	0.293	0.275	0.305
VARIABLES	lnwage in 2015			
Cog/Noncog skills measured in	2000	2004	2000	2004
Control for Years of Education	No		Yes	
Cognitive (2000) or literacy (2004)	0.151**	0.0438	0.137*	0.0304
	(0.0677)	(0.0430)	(0.0709)	(0.0443)
Standardized Chinese	0.109	0.0721	0.106	0.0764
	(0.0804)	(0.0521)	(0.0812)	(0.0530)
Standardized math	0.0112	-0.0520	0.00809	-0.0509
	(0.0500)	(0.0527)	(0.0537)	(0.0525)
Internalizing	-0.0169	-0.0104	-0.0215	-0.0138
	(0.0622)	(0.0614)	(0.0644)	(0.0599)
Externalizing	0.0302	-0.122*	0.0365	-0.113
	(0.0680)	(0.0726)	(0.0735)	(0.0729)
Education aspiration	0.0130	-0.0546	0.0123	-0.0617
	(0.0466)	(0.0477)	(0.0470)	(0.0474)
Years of schooling			0.0203	0.0365
			(0.0359)	(0.0363)
Years of experience			0.0132	0.0173
			(0.0330)	(0.0327)
Observations	423	357	423	357
R-squared	0.322	0.352	0.322	0.356
Village FE	Y	Y	Y	Y

Notes: This table reports OLS results restricting sample to those who started working in 2009. We control for interview type dummies, wave I household wealth, father education, mother education, Inverse Mills Ratio correcting for sample attrition, and Inverse Mills Ratio correcting for missing wage. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Restricting to Early Workers: Employer Observation or Employee Match

Dependent Variable	ln hourly wage in 2015							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Those switched occupations				Those did not switch occupatiosn			
Cog/Noncog skills measured in	2000	2004	2000	2004	2000	2004	2000	2004
Control for Years of Education	No		Yes		No		Yes	
Cognitive 2000 or Literacy 2004	0.170*	0.0148	0.160	-0.00456	0.0193	0.264	0.000541	0.223
	(0.0941)	(0.0509)	(0.0995)	(0.0544)	(0.171)	(0.190)	(0.191)	(0.191)
Std Chinese	0.110	0.0932	0.101	0.0963	0.163	-0.0514	0.111	-0.0400
	(0.107)	(0.0723)	(0.109)	(0.0727)	(0.169)	(0.184)	(0.183)	(0.194)
Std math	-0.0562	-0.0540	-0.0661	-0.0588	-0.0498	0.00296	-0.0634	-0.00730
	(0.0644)	(0.0813)	(0.0718)	(0.0798)	(0.137)	(0.209)	(0.145)	(0.197)
Internalizing	0.00437	-0.0467	-0.00149	-0.0318	0.170	0.0495	0.173	0.00525
	(0.0760)	(0.0928)	(0.0787)	(0.0914)	(0.147)	(0.128)	(0.148)	(0.169)
Externalizing	0.0260	-0.0873	0.0336	-0.0873	-0.192	-0.0801	-0.228	-0.0588
	(0.0921)	(0.0934)	(0.0994)	(0.0900)	(0.162)	(0.160)	(0.163)	(0.180)
Edu Aspiration	0.0262	-0.0876	0.0281	-0.104	0.0532	-0.0776	0.0198	-0.102
	(0.0601)	(0.0653)	(0.0604)	(0.0648)	(0.115)	(0.149)	(0.112)	(0.156)
Years of schooling			0.0160	0.0504			-0.0168	-0.115
			(0.0485)	(0.0473)			(0.118)	(0.138)
Years of experience			-0.000390	0.0128			-0.0488	-0.150
			(0.0465)	(0.0440)			(0.114)	(0.131)
Observations	314	264	314	264	133	110	133	110
R-squared	0.386	0.449	0.388	0.460	0.553	0.694	0.567	0.725
Village FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports OLS results restricting sample to those who started working in 2009. We control for interview type dummies, wave I household wealth, father education, mother education, Inverse Mills Ratio correcting for sample attrition, and Inverse Mills Ratio correcting for missing wage. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Correlations between childhood noncognitive measures with 2015 Big Five and Depression

Internalizing/Externalizing in	2000		2004	
Correlations	Internalizing	Externalizing	Internalizing	Externalizing
Depression	0.0332	0.0033	0.0670*	0.0617*
Extraversion	-0.0367	-0.0141	-0.0727*	-0.0414
Agreeableness	-0.0738*	-0.0461	-0.0674*	-0.1113*
Conscienciousness	-0.0201	-0.0144	-0.0668*	-0.0931*
Neuroticism	0.0600*	0.0288	0.0802*	0.0483
Openness	-0.0417	-0.0381	-0.023	-0.0443

Data source: Gansu Survey of Children and Families.
Notes: * indicates that p-value < 0.05.