Maternal education, parental investment and non-cognitive characteristics in rural China

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Abstract

The importance of non-cognitive skills in determining long-term human capital and labor market outcomes is widely acknowledged, but relatively little is known about how educational investments by parents may respond to children's non-cognitive characteristics early in life. This paper evaluates the parental response to non-cognitive variation across siblings in rural Gansu province, China, employing a household fixed effects specification; the non-cognitive measures of interest are defined as the inverse of both externalizing challenges (behavioral problems and aggression) and internalizing challenges (anxiety and withdrawal). The results suggest that there is significant heterogeneity with respect to maternal education. More educated mothers appear to compensate for differences between their children, investing more in a child who exhibits greater non-cognitive deficits, while less educated mothers reinforce these differences. Most importantly, there is evidence that these compensatory investments lead to the narrowing of non-cognitive deficits over time for children of more educated mothers, while there is no comparable pattern in households with less educated mothers. JEL codes: I24, O15, D13. Keywords: non-cognitive characteristics, parental investment, intrahousehold allocation.

1 Introduction

In recent years, both research and policy debates have placed increasing emphasis on the importance of non-cognitive skills in determining long-term economic outcomes. Data primarily from industrialized countries has suggested that non-cognitive skills have a large impact on adult economic

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welfare, measured as earnings and labor productivity (Heckman and Rubinstein, 2001; Heckman, Stixrud and Urzua, 2006; Cunha, Heckman, Lochner and Masterov, 2006; Carneiro, Crawford and Goodman, 2007). Particularly relevant for this analysis, evidence from the sample of rural Chinese youth employed here suggests that non-cognitive skills as measured in adolescence are predictive of school-to-work transitions in early adulthood (Glewwe, Huang and Park, 2017). There are many causal pathways through which stronger non-cognitive skills may lead to improved educational and economic outcomes. Individuals with enhanced skills may be more persistent in achieving strong academic outcomes or building professional expertise, may be more resilient in the face of setbacks, or may be better able to forge useful professional relationships. One particularly important channel, however, is the relationship forged much earlier in life between children and their parents.

Variation in non-cognitive characteristics may affect parental investments in several ways. First, this variation could alter the weight that a parent places on a child's welfare. Parents could favor a child with whom they forge a stronger relationship, or a child who exhibits more behavioral challenges if he requires more nurturing. Second, even if the weights parents place on their children's welfare are unchanged, variation in non-cognitive characteristics could affect children's future income, and may affect the returns to human capital investment in a given child. Depending on whether parents emphasize efficiency or equality, they may invest more or less in human capital development for a child who is struggling or flourishing.

Ultimately, we may observe investment that is compensatory, defined as a pattern in which parents invest more in a relatively weaker child, or investment that is reinforcing, defined as a pattern in which parents invest more in a stronger child. Needless to say, the question of whether investment is in general compensatory or reinforcing is an important question in family economics going back to Becker; Almond and Mazumder (2013) provide a recent review.

The objective of this paper is to analyze whether non-cognitive characteristics measured in childhood and adolescence have a significant impact on the within-household allocation of educational expenditure in rural Gansu province, China. We employ a panel dataset (the Gansu Survey of Children and Families) that provides a detailed set of outcome measures for a large cohort of children in one of the poorest provinces in China. Non-cognitive characteristics are measured via direct surveys of the children, and defined as the inverse of externalizing challenges (behavioral problems and aggression) and internalizing challenges (withdrawal and anxiety); accordingly, our measure effectively captures an absence of behavioral or socio-emotional problems. Focusing on a sample of two-children families, our primary specification examines how parents respond to differences in non-cognitive characteristics conditional on household fixed effects, and whether this response varies based on parental education.

Our results suggest that while parents are not responsive to differences in non-cognitive characteristics on average—neither reinforcing nor compensating for these differences—there is significant heterogeneity with respect to characteristics of the parents, and particularly the mother. House-

holds with more educated mothers show evidence of significantly more compensatory investment compared to households with less educated mothers. For a child who scores one standard deviation lower on the non-cognitive index relative to his sibling (i.e., indicative of more behavioral challenges), an increase in maternal education from the 25th to the 75th percentile, or from one half to six years of education, would ceteris paribus result in an increase in discretionary educational expenditure directed to this child of over 40%. Discretionary expenditure comprises all educational expenditure excluding tuition, and accounts for nearly 40% of total education expenditure; there is no parallel effect observed for tuition.[1] There is also very little evidence of comparable heterogeneity with respect to the education of the father.

The primary challenge faced in this analysis is that non-cognitive characteristics may in fact be endogenous to, or partly an outcome of previous parental investment; if there is some serial correlation in parental investment, this will generate bias toward the detection of a reinforcing pattern of expenditure. We address this challenge in several ways. First, as already noted, we observe a heterogeneous pattern only for maternal education, not for paternal education; this is not consistent with the hypothesis that the observed pattern simply reflects a different distribution of non-cognitive skills in higher socioeconomic status households. Second, we demonstrate that bias on the interaction effect including maternal education will only arise given specific assumptions that do not seem to be supported by the empirical evidence. Third, we present evidence that the results are robust to several alternate specifications, including the use of earlier measurements of non-cognitive characteristics and the inclusion of control variables for past educational expenditure.

In the final section of the paper, we analyze whether this variation in compensatory vis-a-vis reinforcing behavior results in the reduction of non-cognitive deficits over time for children in households with more educated mothers—where struggling children receive greater investment—compared to children in households with less educated mothers. While the second-born child in this data is observed only once, the first-born child is observed three times. Analyzing the longitudinal data observed for the first-born child, we do find evidence of significantly greater catch-up for children of more educated mothers.

As a result, the correlation between maternal education and non-cognitive characteristics becomes more pronounced as children age. In the first wave, the observed cross-household correlation between a dummy variable for a mother of high maternal education and non-cognitive characteristics is essentially zero. By the third wave, this correlation has increased in magnitude to .151. This result highlights the role of maternal education in shaping the formation of non-cognitive skills, consistent with the broader literature on the importance of maternal education in child development (Carneiro et al., 2013; Currie, 2009). Moreover, if the economic returns to non-cognitive

[1] We also find some evidence of a similar pattern for cognitive skills as captured by test scores on a Chinese achievement test: less educated mothers invest more in children with stronger cognitive skills, while more educated mothers compensate children characterized by weaker skills. However, we preferentially focus on non-cognitive skills given that we feel this is a more significant contribution to the existing literature.

skills are significant, differential parental compensation is a channel through which inequality across households can widen over time.

Our paper contributes to several related literatures on intrahousehold allocation and human capital investment. First, there is an extensive literature examining parental responses to differences in children's endowment, and the evidence has been mixed. Bharadwaj et al. (2013b), Royer (2009), and Almond and Currie (2011) find little or no evidence of either compensatory or reinforcing behavior. Akresh et al. (2012), Rosenzweig and Zhang (2009), Frijters et al. (2013), Almond et al. (2009), Adhvaryu and Nyshadham (2014) and Aizer and Cunha (2012) find parents exhibit reinforcing behavior in Burkina Faso, China, Sweden, Tanzania, and the United States, while Del Bono et al. (2012) find evidence of compensatory behavior in breast-feeding decisions and birth weight and Black et al. (2010) provide some indirect evidence of compensatory behavior in a robustness check. Bharadwaj et al. (2013a) find compensatory investment with respect to initial health comparing across siblings, but comparing across twins, there is no evidence of either compensatory or reinforcing behaviors. Leight (2017) finds evidence of compensatory behavior with respect to height-for-age using the same sample as this paper.

This literature, however, focuses primarily on parental responses to children's health endowment and cognitive ability. Our paper is one of the first papers that examines whether parents respond to children's non-cognitive characteristics in the allocation of human capital investment.[2] While we will also provide some evidence of heterogeneity across households characterized by different maternal education levels in their response to cognitive skills, we focus primarily on the response to non-cognitive skills given the absence of evidence in this area.

Second, our paper finds that maternal education plays an important role in determining the allocation of parental investment. This is similar to the results reported in Hsin (2012) and Restropo (2016), who conclude that households with less educated mothers generally exhibit reinforcing investment behavior, while households with more educated mothers exhibit compensatory behavior. However, neither of these papers examine the father's education level; instead, they analyze maternal education as a proxy for household socioeconomic status. In light of these findings, a recent review by Almond and Currie (2011) suggests that the observed pattern could be due to credit constraints in low socioeconomic status households, or a high elasticity of substitution between consumption and human capital investment in these households.

In our context, we are able to rule out these two channels given the absence of any evidence of heterogeneity with respect to the father's education and household income. Accordingly, our paper constitutes suggestive evidence that there may be another channel through which maternal education affects the allocation of expenditure between children (i.e., different maternal preferences, or greater maternal bargaining power).

[2]The only other relevant paper is Gelber and Isen (2013). While it is not the focus of their work, they report in their appendix that parents respond positively to a child with greater observed non-cognitive abilities, but they do not further investigate the heterogeneity with respect to maternal education.

Third, there is growing evidence that early intervention and investment can mitigate initial deficits in children's endowments (Adhvaryu et al., 2015; Almond et al., forthcoming; Bhalotra and Venkataramani, 2016; Bleakley, 2010; Cunha and Heckman, 2007; Cunha et al., 2010; Gould et al., 2011; Kling et al., 2007). However, this literature primarily focuses on catch-up in children's health and cognitive outcomes. To the best of our knowledge, we are the first to show evidence of the narrowing of non-cognitive deficits as a result of parental investment.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 describes the empirical strategy and the primary results, and Section 4 examines the longitudinal evidence. Section 5 concludes.

2 Data

The data set used in this paper is the Gansu Survey of Children and Families (GSCF), a panel study of rural children conducted in Gansu province, China. Gansu, located in northwest China, is one of the poorest and least developed provinces in China. The description of the data here draws substantially on the description in Leight, Glewwe and Park (2014).

The first wave of the GSCF was conducted in 2000, and surveyed a representative sample of 2,000 children aged 9–12 in 20 rural counties, supplementing these surveys with additional surveys of mothers, household heads, teachers, principals, and village leaders. These children are denoted the "index children." All but one of the index children have complete information in the first wave.

The second wave, implemented in 2004, re-surveyed the first sample of children at age 13–16 and also added a survey of their fathers. 1,872 children, or 93.6% of the original sample, were re-interviewed in the second wave. In addition, surveys were added of the eldest younger sibling of the index child. These additional children are denoted "younger siblings." Surveys are conducted directly with the younger siblings, as well as with their homeroom teachers; in addition, mothers and fathers report limited supplementary information about the younger siblings.

In early 2009, a third wave of surveying was conducted, re-interviewing the index children during Spring Festival, a period at which many of them had returned to their natal villages. In cases where the sampled individual was not available, parents were asked to provide information about their child's education and employment status. 1,437 individuals, or 72% of the original sample, were interviewed directly in this wave, and information was collected in parental interviews for an additional 426 sample children.

The household surveys in waves one (2000) and two (2004) included extensive questions about schooling outcomes, household expenditure on education for each child, time investments in education by parents and teachers, and child and parental attitudes, as well as more standard socioeconomic variables. The index children also completed a number of achievement and cognitive tests. Younger siblings also completed these tests in wave two.

In addition, each wave of data collection included survey questions posed to the sample children that were designed to measure their non-cognitive characteristics. In the first and second waves, the survey measured both internalizing and externalizing behavioral challenges: the former refers to intra-personal problems (e.g., withdrawal and anxiety), and the latter to inter-personal problems (destructive behavior, aggression, and hyper-activity). Both measures of non-cognitive characteristics are constructed by recording the respondent's agreement or disagreement with a series of statements and then applying item response theory (IRT) to generate internalizing and externalizing scores. The measures are identical across waves one and two, and the scores are standardized to have a mean of zero and a standard deviation of one. In the third wave, a Rosenberg self-esteem index and a depressive index were measured. Further detail about the construction of the non-cognitive characteristics measures can be found in Glewwe, Huang and Park (2017).

It may be useful to briefly comment here on the measures of non-cognitive characteristics employed (and the terminology used to describe these measures), and their relationship to the previous literature. A number of other papers have employed variables capturing internalizing and externalizing challenges, including Heckman et al. (2013) in analyzing the long-term effect of the Perry preschool program, and Neidell and Waldfogel (2010) in analyzing cognitive and non-cognitive peer effects in preschool education. Similarly, Bertrand and Pan (2013) and Cornwell, Mustard and Van Parys (2013) document gender differences in a number of non-cognitive measures including internalizing and externalizing indices, and Juhn, Rubinstein and Zuppann (2015) employ a behavioral problems index in analyzing quality-quantity trade-offs. The terminology used to describe these measures varies, but given that we are not measuring a non-cognitive skill per se (e.g., self-esteem, or negotiating ability), we will follow the other authors noted here and preferentially use the term non-cognitive characteristics.[3]

Non-cognitive characteristics of the younger siblings were measured only in wave two, and thus wave two will be the primary source of the data employed. For ease of interpretation, the internalizing and externalizing indices have been inverted for analysis have been inverted; in the original index, a higher value indicates more challenges, but in our index a higher value indicates fewer challenges.

Our analysis uses a subsample of the families in the survey: those with two children in the household where both children have reported measurements for non-cognitive and cognitive skills in the second-wave survey. The measures of cognitive skills employed are scores on grade-specific mathematics and Chinese achievement tests that were developed, administered and scored by the survey management team. (Data on grades received by the sample children in school is also available, but we find that there is little variation in these reported grades, consistent with qualitative evidence that grades are not a meaningful signal of achievement in Chinese primary schools in rural

[3]Evidence in psychology suggests that positive attributes such as conscientiousness, agreeableness, and openness to experience are negatively correlated with the internalizing and externalizing behaviors we analyze here (Ehler et al., 1999).

areas.) Accordingly, we use the achievement test scores as a proxy for cognitive skills.

If the index children and the younger sibling are the only children in the household, then the surveys provide a complete overview of parental allocations and child endowment. Complete data is available for 816 children (408 households) drawn from 90 localities in 20 counties, and these households constitute the relevant subsample. In our sample, only 6.5% of households have one child. The remaining households are excluded because the index child has two or more siblings, or has one older sibling for whom non-cognitive characteristics are not reported. In the robustness checks reported in Section 3.2, we will also present results employing a larger sample including households where these two children (the index child and the younger sibling) are part of a larger family.[4] Figure 1 summarizes the structure of the sample, including the years in which data is collected, the children observed in each wave, and their age at the point of data collection.

Panel A of Table 1 reports summary statistics for the subsample of two-children families and the overall sample for key demographic indicators, as well as a t-test for equality between the two means; the covariates reported are measured in the second wave of the survey, the wave in primary use here. It is evident that there are no significant differences in income or parental education between the sample and the subsample. However, households in the subsample are slightly younger and have younger children. This primarily reflects the exclusion of larger families or families in which the index child is the younger child, as these families are generally headed by older parents. Importantly, there are also no significant differences detected in the index child's non-cognitive characteristics.

The dependent variable of interest is educational expenditure per child per semester, reported by the head of household in six categories: tuition, educational supplies, food consumed in school, transportation and housing, tutoring, and other fees.[5] Each household separately reports expenditure for each child in each of these categories. Our analysis will focus on tuition and discretionary expenditure, defined as the sum of all expenditure excluding tuition. Summary statistics for average expenditure per child for the subsample of families analyzed can be found in Panel B of Table 1. Total educational expenditure averages around 360 yuan per child per semester, and an average of 20% of household income is allocated to educational expenditure in total for both children.

We focus on educational expenditure given that it is the primary form of child-specific expenditure reported in this dataset. The only other type of child-specific expenditure reported is medical expenditure over the past year; only 25% of households report any positive medical expenditure for either child over the past year, and unsurprisingly this expenditure is highly correlated with reported illness (i.e., it is reasonable to assume that very little corresponds to preventive care).

[4]While China's One-Child Policy was in effect during the period in which these children were born, many rural households could nonetheless have two children legally under various exemptions to the policy (Gu et al., 2007). It is not possible using this dataset to accurately identify for each household whether it was in technical compliance with the policy.

[5]In China, textbook fees are mandatory and levied as part of the overall tuition, and here they are likewise reported in the tuition category. Educational supplies is supplies other than textbooks.

Given that we are primarily interested in human capital investments with long-term returns, we do not focus on medical expenditure. In addition, while parents report the amount of time they invest in childcare in aggregate, they do not report the division of this time between children; accordingly, time investment cannot be used as a dependent variable.

Finally, it may be useful to briefly comment on the advantages and disadvantages of this data source, and the external validity of results examining families with more than one child in China. Clearly, the average size of a household is significantly lower in China relative to other developing countries. However, recent evidence suggests average fertility per woman in rural China is 2.1, suggesting the majority of households do have more than one child, and in that sense our sample of two-child families is by no means unusual (Ding and Hesketh, 2006). In addition, there are very few panel datasets in developing countries that report non-cognitive and cognitive skill measures for multiple children in the same household (enabling the use of a household fixed effects specification), as well as some measures of non-cognitive skills over time. The richness of the human capital measurement in the GSCF renders this data uniquely valuable for our analysis.

3 Empirical strategy and results

3.1 Empirical strategy

Our empirical strategy entails evaluating whether parental expenditure on education for children is correlated with measures of non-cognitive characteristics, conditional on household fixed effects.[6] In other words, our primary specification identifies whether parents are more likely to invest in a child who has more desirable non-cognitive characteristics, relative to a sibling.

The child's observed non-cognitive characteristics will be denoted $Ncog_{ihct}$, for child i in household h, living in county c and born in year t; the non-cognitive variables employed will include the externalizing and internalizing indices, as well as a summary measure that is the mean of the two indices. All non-cognitive variables have been standardized to have means equal to zero and standard deviations equal to one. Again, to facilitate interpretation, the indices have been inverted such that a higher value is indicative of fewer non-cognitive challenges.

The dependent variable, educational expenditure, is denoted Y_{ihct}. The specification includes household fixed effects η_h, year-of-birth fixed effects ν_t, and a vector of child covariates X_{ihct}, including gender, the sibling's gender, birth parity (i.e., whether a child is first-born or second-born), height-for-age, and achievement test scores. The inclusion of birth parity is particularly important, given the evidence presented by Black et al. (2005a) that birth order is an important determinant of children's outcomes. Our sample is comprised of 60% boys and 40% girls.[7]

[6] Given that our primary interest is examining how parents allocate resources between children with different non-cognitive characteristics, it is necessary to include family fixed effects since we are examining within household variation. Also, the use of fixed effects addresses the challenge of unobserved household-level heterogeneity.

[7] For concision, we will employ male pronouns.

This specification is estimated with and without interactions with parental education S_{hct}. Standard errors are clustered at the village level in all specifications; our sample includes 90 villages.

$$Y_{ihct} = \beta_1 Ncog_{ihct} + \beta_2 Ncog_{ihct} \times S_{hct} + X_{ihct} + \nu_t + \eta_h + \epsilon_{ihct} \tag{1}$$

The identification assumption for this family of specifications requires that non-cognitive characteristics are uncorrelated with other unobservable variables that determine parental allocations. This assumption would be violated, for example, if parents invest more in a favored child, who is subsequently observed to score highly on the non-cognitive indices employed.

In order to present some preliminary evidence about the relationship between non-cognitive characteristics and child characteristics conditional on household fixed effects, the following specifications can be estimated, regressing the internalizing and externalizing indices on child covariates X_{ihct} conditional on household fixed effects.

$$Ncog_{ihct} = \beta_1 X_{ihct} + \eta_h + \epsilon_{ihct} \tag{2}$$

The results can be found in Table 2: Panel A reports the correlations with sibling parity, age, gender, and grade level, and Panel B reports the correlations with various measures of the child's endowment. Interestingly, in Panel A there is no evidence of any significant correlation between the internalizing index and any child characteristic. However, for the externalizing index we observe that non-cognitive measures are lower, suggestive of more behavioral challenges, for second-born children, younger children, boys and children enrolled in lower grades in school. There is, of course, a high degree of correlation among these covariates: second-born children are on average younger, enrolled in lower grades, and more likely to be boys.[8] Columns (9) and (10) show the results of a multiple regression including all four covariates; there is some evidence here that the most robust correlations are between gender and grade level and the externalizing index. Panel B shows that there is little evidence of significant correlations between non-cognitive characteristics and height-for-age and math and Chinese test scores, though there are weakly significant and negative correlations between the Chinese and mathematics test scores and the internalizing index, and a weakly significant and positive correlation between height-for-age and the externalizing index.[9]

In light of these results, the primary specifications all include year-of-birth fixed effects as well as controls for gender, sibling's gender, sibling parity, height-for-age, and mathematics and Chinese test scores as measured in the second wave, contemporaneously with non-cognitive characteristics.[10] The inclusion of grade fixed effects is more complex, given that grade level can plausibly be considered an outcome. However, we will demonstrate that the primary results are robust to the

[8] The implications of gender selection for this analysis will be explored in greater detail in Section 3.3.

[9] Test scores are normalized to have mean zero and standard deviation one employing the grade-specific mean and standard deviation. These specifications also include controls for gender, sibling parity and grade fixed effects.

[10] For test scores, we include both the raw test score and the score normalized by grade level to have mean zero and standard deviation one.

inclusion of grade fixed effects.

Given that the primary specifications are estimated conditional on household and year-of-birth fixed effects, it is also useful to examine how much variation in the child characteristics of interest is observed within a given household and within a given birth year. In the on-line appendix, we report the R-squared from a series of simple regressions including only the specified fixed effects as explanatory variables and various child covariates as the dependent variable.[11] In general, between 50% and 60% of the variation in non-cognitive characteristics is explained by household fixed effects, suggesting there is still considerable within-household variation.

3.2 Primary results

Table 3 presents the results of estimating equation (1) without the interaction terms with parental education. The objective is to test whether parental allocations of educational expenditure are responsive, on average, to variation in non-cognitive characteristics between siblings; the measures of expenditure employed are tuition and discretionary expenditure. Enrollment is near universal in the core sample (only 3% of children are reported not enrolled), and thus school enrollment is not reported as an outcome. Each specification is estimated both with and without control variables, and employing the internalizing and externalizing index in turn as independent variables, as indicated in the final row of the table.

The results show coefficients that are small in magnitude, varying in sign, and generally insignificant. This suggests that parents are neither systematically compensating children characterized by more internalizing and externalizing challenges, nor systematically reinforcing these differences. (A similar pattern is observed if we estimate these specifications without household fixed effects.)

In light of this evidence, we then examine whether parents who themselves have certain characteristics are more likely to respond to measured differences in the non-cognitive traits of their children. The most obvious relevant characteristic is education, particularly given that recent work from Hsin (2012) and Restropo (2016) suggests that maternal education is an important determinant of parental allocation of expenditure. While the average level of education reported is relatively low—four years for mothers and seven years for fathers—there is considerable variation. Around 75% of mothers report completing at least one year of formal schooling, and 16% report completing junior high school. For fathers, around 90% report completing at least one year of formal schooling, and 10% report completing senior high school.

Figure 2 shows histograms of the distribution of both maternal and paternal education. The correlation between maternal and paternal education is positive, but low in magnitude (around .3). In addition, Figures 3a and 3b show the distribution of intrahousehold (between-sibling) differences in non-cognitive characteristics and in normalized expenditure residuals for households at different levels of maternal education. We can observe that the mean absolute difference in non-cognitive

[11] The on-line appendix is available on both authors' homepages.

characteristics between siblings is around .75 standard deviations, and this is roughly constant across households of different levels of maternal education. Normalized expenditure residuals are calculated by regressing expenditure on child characteristics (gender, birth parity, cognitive skills, and height-for-age), generating the residuals and standardizing them to have mean zero and standard deviation one. The mean absolute difference is around .4 standard deviations, and this seems to be larger at higher levels of maternal education.

To identify whether parents who are more educated respond differentially to differences in non-cognitive characteristics, we then re-estimate equation (1) including interaction terms between non-cognitive indices and parental education. Again, we estimate a specification that includes controls for a wide range of child characteristics, as well as the interactions of gender, age, sibling parity, height-for-age and Chinese and mathematics scores with the specified measure of parental education. We also report a simpler specification that is unconditional on child characteristics.

The results are reported in Table 4 for maternal education and Table 5 for paternal education. We observe a robust pattern in which households in which mothers have low levels of education (approximately fewer than three years of schooling) allocate more discretionary educational expenditure to children with higher non-cognitive scores, reinforcing the pre-existing differences, while households with more educated mothers seem to engage in compensatory behavior, allocating more expenditure to children characterized by lower scores and thus by more behavioral and socio-emotional challenges. This is evident in the negative coefficients on the interaction term between non-cognitive indices and maternal education in Columns (1) through (4) of Table 4.[12]

By contrast, there is no compensatory effect observed for tuition in Columns (5) through (8) of the same table, consistent with the intuition that tuition is not easily manipulable; though the coefficients are negative, they are small in magnitude and insignificant.[13] Comparing the estimated coefficients for the interaction effect in Columns (1) and (5), we observe that relative to the mean of the dependent variable, the magnitude of the coefficient on tuition in Column (5) is around 5% of the magnitude of the coefficient on discretionary expenditure in Column (1). A similar pattern is observed when comparing the coefficients estimated in the other parallel specifications.

Turning to paternal education, the interaction terms reported in Table 5 are small in magnitude, heterogeneous in sign, and generally insignificant. In addition, it is evident in both tables that the results from the specifications including a full set of control variables and the more parsimonious specifications are highly consistent. Thus while there may be some concern that contemporaneous measures of cognitive skills and health are endogenous relative to parental investments, there is no evidence that including these variables as controls generates systematic bias.

The bottom row of Table 5 reports p-values testing the equality of the estimated coefficients

[12] Aizer and Cunha (2012) find that the degree of parental reinforcing behaviors increases with family size. However, our finding cannot be explained by variation in family size since the sample is restricted to only two-child households.

[13] Approximately 12% of students attend schools that are private or publicly assisted private institutions; accordingly, it is possible that there is some variation in tuition, and some potential for parents to select a higher-tuition school for their children.

on the interaction terms for maternal and paternal education for the two non-cognitive indices, respectively.[14] These coefficients are denoted β_2^m and β_2^f, where β_2^m refers to the coefficient on the interaction term for maternal education, and β_2^f refers to the analogous coefficient for paternal education. We can reject the hypothesis that β_2^m and β_2^f are equal in all specifications employing discretionary expenditure as the dependent variable. We also report results from a joint test of the hypotheses $\beta_1^m = \beta_1^f$ and $\beta_2^m = \beta_2^f$, and find parallel results.

Examining the coefficients on the interaction terms for other child characteristics, we can observe that they are generally insignificant. For cognitive skills as captured by the test score in Chinese, there is a parallel pattern to that observed for non-cognitive skills: the coefficient on the level term is positive and the coefficient on the interaction term is negative, though both are noisily estimated. For the test score in mathematics and height-for-age, by contrast, the coefficients are heterogeneous in sign and generally insignificant. We hypothesize that this difference primarily reflects the fact that Chinese language ability may be readily observable by parents, while ability is mathematics may be largely unobservable; in addition, parents may not receive an accurate signal of their children's ability based on their school performance, given the evidence previously presented that there is very little variation in grades. Accordingly, their ability to respond to their children's mathematics proficiency may be limited.

Finally, the magnitudes of the implied effects for non-cognitive characteristics are substantial. For example, consider a child whose score on the internalizing index is one standard deviation lower than his sibling's score, suggestive of more behavioral or socio-emotional challenges. The coefficient on the interaction term suggests that an increase in maternal education from the 25th to the 75th percentile, or from one half to six years — conditional on other household characteristics — would yield an increase in discretionary educational expenditure for this child compared to his sibling of over 40%. The magnitudes are similar for the coefficients estimated for the externalizing index.

Why do parents utilize educational expenditure as a tool to address non-cognitive deficits? We should note that we cannot rule out that parents are simultaneously making other, targeted investments, in expenditure or in time; as previously highlighted, educational expenditure is the only type of child-specific investment reported in this survey other than medical care. However, given that these are relatively resource-constrained households, forms of expenditure that might be considered appropriate for addressing non-cognitive deficits in a developed county (e.g., therapeutic interventions, or intense attention by parents or teachers) may be unavailable, leading households to use educational expenditure as a preferred mechanism of compensation.

Alternate specifications To explore the robustness of these results, we re-estimate our primary specification using two alternate samples. First, we employ the full sample of all households where the number of children is greater than or equal to two, rather than restricting to households in

[14] This test is implemented by estimating the two specifications simultaneously in a seemingly unrelated regression framework.

which the index child and his or her younger sibling are the only children.[15] (Less than 10% of the sample of interest are households with only one child.) Second, we restrict the sample to households reporting a first-born son. It should be noted that gender cannot be considered to be exogenous in this sample; nearly 70% of second-born children are boys. However, consistent with existing anthropological evidence, there is little evidence of sex selection prior to the first birth or after the birth of a son, as the gender ratios observed among first-born children and second-born children following a son are not significantly different from .5 (Gu et al., 2007). Accordingly, the distribution of gender within households with first-born sons is plausibly exogenous.

The results can be found in Panel A of Table 6. Columns (1) through (4) report the estimated coefficients for discretionary expenditure, focusing first on the larger sample and then on the gender-restricted subsample, and Columns (5) through (8) report the results for tuition. For concision, all robustness checks use the summary non-cognitive measure that is the mean of the internalizing and externalizing indices, and report the fully saturated specification including all controls. We can observe that the interaction terms on maternal education are consistently negative and and of roughly equal magnitude, while there is again no significant heterogeneity with respect to paternal education. Households in which the index child has only an older sibling are still not observed in the larger sample due to the absence of data on this sibling. However, again the evidence presented in Table 1 suggests that there is no significant difference in household characteristics or the index child's non-cognitive characteristics when comparing the subsample to these excluded households.[16]

We also verify that the primary results are robust to a number of additional specifications, focusing now on the estimated interaction effects for maternal education. We re-estimate the primary specification including grade fixed effects; utilize log expenditure as the dependent variable; reformulate the non-cognitive index as a percentile rank variable; and use an alternate measure of non-cognitive skills derived from teacher reports.[17] The results as reported in Panel B of Table 6 are all consistent in both sign and significance. In the on-line appendix, we report additional specifications in which we use the difference between maternal and paternal education interacted with the non-cognitive index as the independent variable, and also restrict the sample to households where parents have relatively similar education levels. In both cases, the interaction effects remain

[15] We preferentially employ the restricted sample in the primary results given that failing to observe the endowment of the third sibling may lead to attenuation bias in the primary results if parents are compensating the unobserved sibling.

[16] We also explore whether there is evidence of a correlation between birth spacing (between the first- and second-born child) and maternal education that could be an alternate channel for the detected pattern. There is no evidence of any correlation between birth spacing and maternal or paternal education, and no evidence that parents respond differentially to non-cognitive characteristics in households with different spacing between the two siblings.

[17] The other relevant measure of non-cognitive skills available in our data is drawn from surveys of the children's teachers, who are asked to report whether a child possesses a series of eight characteristics, both positive and negative. This series includes whether the child is smart, conscientious, reasonable/well-mannered, clean, enjoys work, is lively/imaginative, gets along with others, likes to cry, or lacks confidence. Given the limited variation in this measure, which has only eight unique values, we construct a dummy variable equal to one if the teacher's reports of the child's characteristics places him or her in the top half of all children, denoted $Tcog^{D}_{ihct}$. Teacher surveys are not available for a small number of sampled children.

significant and negative.

3.3 Bias due to serial correlation and socioeconomic status

The primary challenge for our empirical results is that measured non-cognitive skills may be endogenous to previous parental investment: children who have previously been favored with more parental investment may show evidence of higher non-cognitive skills. If there is then some serial correlation in investment, this may be a source of bias in our results. Consider the following simple specification as an example, where the dependent variable is educational expenditure and $Y_{i,t-1}$ denotes previous parental investment.

$$Y_{it} = \beta_1 Noncog_{it} + \beta_2 Y_{i,t-1} \tag{3}$$

If we assume that prior investment is unobserved and is positively correlated with expenditure today, then $Cov(Noncog_{it}, Y_{i,t-1}) > 0$, generating upward bias on the coefficient β_1. If β_1 is positive (i.e., investment is higher for children with higher non-cognitive scores), then we will over-estimate the degree of reinforcing investment. If β_1 is negative (i.e., investment is higher for children with lower non-cognitive scores), then the coefficient will be biased toward zero. The bias can be captured by the familiar term for omitted variables, $\frac{\beta_2 \ Cov(Y_{i,t-1}, Noncog_{it})}{Var(Noncog_{it})}$, where β_2 captures the degree of serial correlation in investment.

The question of primary interest for our specification is whether there will be bias in the interaction term between non-cognitive indices and maternal education – and, if the bias does exist, why do we observe this pattern only for maternal education, but not paternal education? If we estimated equation (3) separately for low-education and high-education mothers and then calculated the difference in the estimated correlations β_1 as a proxy for the interaction term, the bias would cancel unless $\frac{\beta_2 \ Cov(Y_{i,t-1}, Noncog_{it})}{Var(Noncog_{it})}$ is different for the two samples. This could arise if either the variance in non-cognitive scores or the degree of serial correlation in investment is different for more and less educated mothers (i.e., β_2 is not the same), or if the relationship between past investment and current non-cognitive characteristics is different for more and less educated mothers (i.e., the returns to investment are not the same).

We can present some evidence on these points using data reported on non-cognitive characteristics and expenditure for the first-born child over time. In general, there is positive serial correlation in investment that seems to be significantly larger in families with more educated mothers.[18] However, there is no evidence that the dependence of current non-cognitive scores on past investment differs significantly in households with more educated mothers, and there is also no evidence that $Var(Noncog_{it})$ is statistically different between the two groups. Thus if anything, the upward bias on β_1 would be larger in the sample of more educated mothers, generating upward bias on the

[18] More specifically, the correlation between $Y_{i,t-1}$ and Y_{it} is 0.22 for children with mothers above the median level of education, and 0.11 for children with mothers below the median level of education.

interaction term of interest; this is, of course, in the opposite direction of the observed effect.

We also conduct additional tests to evaluate the potential for bias in the primary specifications due to serial correlation in investment. First, we presume that there is limited scope for parental investment to affect non-cognitive characteristics prior to primary school, and thus construct a new variable $Ncog_{ihct}^{prim}$ that is defined as non-cognitive characteristics at primary school age, as observed in wave one for the older sibling or wave two for the younger. (We similarly define expenditure at primary school age Y_{ihct}^{prim}.) We can then re-estimate a specification parallel to the main specification employing the primary school non-cognitive variable as the independent variable.[19] Second, we re-estimate our primary specification controlling directly for lagged expenditure.

Another potential source of bias in these results is the fact that maternal education may proxy for household income. As suggested by Almond and Currie (2011) and Conley (2008), low socioeconomic status households may invest more in better endowed children due to credit constraints; alternatively, the elasticity of substitution between consumption and human capital investment could be higher for low SES households. These hypotheses are somewhat less plausible in our context given that there are no parallel effects for paternal education, and there is no evidence that maternal education is more closely correlated with household income when compared to paternal education in this sample. However, we can also test this channel by including additional interaction terms for household income and fixed assets in our primary specification.

The results from all four robustness checks are reported in Panel C of Table 6. We observe generally consistent coefficients comparing across the four specifications analyzed (primary age measures of non-cognitive skills, controls for lagged expenditure, inclusion of income interacted with non-cognitive skills, and inclusion of fixed assets interacted with non-cognitive skills). In addition, the interaction terms with income and assets are uniformly insignificant.

While the coefficients estimated when employing the primary-school measures of non-cognitive skills (Columns 1 and 5) are generally smaller in magnitude, the mean levels of expenditure are also lower when we examine only children at primary school age. The estimated coefficients suggest that a one standard deviation increase in maternal education leads to an increase in discretionary expenditure directed to a child characterized by a non-cognitive index that is one standard deviation lower of around 33%, compared to an effect size of over 40% using the original specification. The fact that the magnitudes of the observed effects are generally consistent across these four specifications suggests that endogeneity of non-cognitive skills does not pose a significant source of bias.

4 Catch-up over time

Given the evidence about compensatory investment in households with educated mothers, it is plausible to hypothesize that over time, children of educated mothers experiencing more non-

[19] Rather than year-of-birth fixed effects, we use fixed effects for the age of the child in the survey year.

cognitive challenges should begin to catch up relative to their peers (assuming, of course, that there are positive returns to educational expenditure). In other words, the persistence over time of the internalizing and externalizing measures should be weaker for children of educated mothers.

In this data, the younger sibling is only observed once (in the second wave of the survey employed here), while the older sibling is observed in all three survey waves. Accordingly, to test whether catch-up is more evident in more educated households, we examine whether the longitudinal correlation in child characteristics for the older child is weaker in households with a more educated mother.[20] More specifically, we regress various measures of non-cognitive characteristics observed in 2009 and 2004 on earlier measures for the same child. In 2009, the psychometric measures include a Rosenberg index of self-esteem, and an index of depression.[21] In 2004, internalizing and externalizing indices are reported as already noted; in 2000, the internalizing and externalizing indices are reported, as well as a self-esteem measure.

In the psychology literature, it is also common to use rank-order measures for personality traits (Shiner and Caspi, 2003; Roberts and DelVecchio, 2000). This is particularly relevant when employing longitudinal data in which subjects are observed at very different ages. Accordingly, for this analysis we convert all the non-cognitive measures into percentile measures ranking the child with respect to children of the same gender and the same age group; the child with the strongest non-cognitive characteristics is assigned the highest percentile of 1.[22]

These measures will be denoted $Psych_{ihct}$ for child i in household h in county c born in year t, and the superscript will indicate the year in which the data was observed. Thus the primary equations of interest can be written as follows, regressing non-cognitive outcomes on outcomes from the previous wave and the interaction of the previous outcome with a household-level input, I_{hct}. I_{hct} can be a dummy variable for the mother or father having a high level of education (above the median), or reported discretionary educational expenditure on the child in the previous wave. The specifications of interest are written as follows.

$$\begin{aligned} Ncog_{ihct}^{2009} &= \beta_1 Ncog_{ihct}^{2004} + \beta_2 Ncog_{ihct}^{2004} \times I_{hct} \qquad (4) \\ &+ \beta_4 X_{hct} + \nu_t + \kappa_c + \epsilon_{ihct} \\ Ncog_{ihct}^{2004} &= \beta_1 Ncog_{ihct}^{2000} + \beta_2 Ncog_{ihct}^{2000} \times I_{hct} \qquad (5) \\ &+ \beta_4 X_{hct} + \nu_t + \kappa_c + \epsilon_{ihct} \end{aligned}$$

[20] Another test that could be implemented is to examine whether the absolute difference in human capital characteristics between the first-born and second-born children is narrower in wave two in households with more educated mothers. This would be consistent with compensatory investment already successfully leading to "catch-up" by the weaker sibling. This test shows no significant differences in the absolute difference comparing across households with more or less educated mothers. Results are reported in the on-line appendix.

[21] We invert the depression index, such that a higher depression index is indicative of a lower level of depression.

[22] The primary results are similar when estimated employing the original variables, though more noisily estimated.

X_{ihct} denotes a vector of child- and household-level controls, and standard errors are clustered at the village level. The control variables are drawn from the same set of covariates employed in the earlier analysis: math and Chinese test scores as measured in 2004, height-for-age as measured in 2004, household net income, fixed capital and assets as measured in 2004, paternal and maternal education dummies, the number of siblings in the family, gender, gender of the younger sibling, sibling gender interacted with the number of siblings, and county and year-of-birth fixed effects. We also include an interaction term with household net income as measured in 2004. In the specifications including an expenditure interaction effect, additional controls include linear and quadratic terms for total and discretionary educational expenditure, and a dummy for discretionary expenditure above the median.

The results of estimating equations (4) and (5) for maternal and paternal education dummies and educational expenditure are reported in Table 7. Note a positive coefficient β_1 can be interpreted as evidence of persistence of non-cognitive characteristics over time, and a negative coefficient β_2 can be interpreted as catch-up in households with higher levels of parental education or more educational expenditure. The interaction terms with maternal and paternal education are included in the same specification.

First, it is useful to note that non-cognitive characteristics at ages 9–12 (measured in 2000) do not seem to be particularly strongly correlated with the measures collected at ages 13–16 (measured in 2004); β_1 is positive, but not always statistically significant. There appears to be greater evidence of persistence between ages 13–16 and young adulthood, or between 2004 and 2009.

Second, and more importantly, there is also evidence, albeit somewhat noisy, of catch-up for children of more educated mothers (as reported in Columns 1, 3, 5, and 7), and for children who receive more educational expenditure (as reported in Columns 2, 4, 6, and 8). This is observed both between 2000 and 2004 and between 2004 and 2009, and is consistent with compensatory investment by mothers facilitating catch-up by children experiencing greater non-cognitive challenges.[23] This pattern is also consistent with the existing literature suggesting non-cognitive skills are more malleable for a longer period into adolescence and young adulthood than cognitive skills (Borghans et al., 2008). (It is, however, important to be cautious in interpreting these results as evidence of returns to the specific investments observed: more educated mothers may also make additional, unobserved investments targeting children with greater non-cognitive challenges that lead to catch-up.)

The interaction terms with paternal education, by contrast, are generally positive and insignificant. Given that there was little evidence that more educated fathers compensated children experiencing more non-cognitive challenges with additional investment, this result is unsurprising.

An alternate test that captures the same fundamental empirical pattern examines the cross-household correlation between non-cognitive characteristics and a dummy variable for the household

[23] Interesting, there is no evidence of comparable catch-up in cognitive skills.

being characterized by high maternal education, conditional on the same set of control variables. This correlation is increasing in magnitude in each wave: in the first wave, it is essentially zero. In the second wave, the correlation has increased in magnitude to .028, and by the third wave, .151. The difference between the first- and third-wave coefficients is statistically significant at the five percent level. There is no evidence of a comparable pattern for paternal education.

Given this pattern, it is also useful to briefly reconsider our primary results of heterogeneous response to variation in non-cognitive characteristics with respect to parental education. The longitudinal evidence suggests that in households with more educated mothers, compensatory investments may already have succeeded in generating some catch-up among first-born children with greater non-cognitive deficits prior to wave two. However, we have already presented evidence in section 3.3 (Table 6) that the primary results are robust to employing the initial, wave one measure of non-cognitive characteristics for the older child. In addition, any catch-up prior to wave two would lead to a narrowing of the gap in non-cognitive scores between children of an educated mother, and thus lead us to underestimate the compensatory behavior engaged in by these mothers. There is no obvious source of bias that would lead us to erroneously conclude that educated mothers are compensating when in fact they are reinforcing.

Considering the long-term effect of the observed patterns, we can again compare a child with a mother below the median level of education to a child with a mother above the median level of education. For the former child, a one standard deviation decrease in the non-cognitive percentile rank in adolescence leads to a .23 decrease in the Rosenberg percentile rank in young adulthood (i.e., the child has lower self-esteem).[24] For the latter child, however, the same decrease in the non-cognitive index in adolescence does not lead to any statistically significant change in self-esteem in adulthood. If there are positive returns in the labor market to non-cognitive skills such as self-esteem — and previous evidence reported in Glewwe et al. (2017) suggests that non-cognitive skills are in fact correlated with school-to-work transitions in this context — this pattern may have meaningful economic implications.

5 Conclusion

The decisions parents make about how to allocate educational investments among children have major implications for policies targeting human capital accumulation. As greater emphasis is placed on the development of non-cognitive skills as well as cognitive skills as a strategy for increasing long-term welfare, it is even more important to understand how parents may respond to observed differences in non-cognitive skills, and whether they seek to address any detectable deficits.

The evidence in this paper suggests that in a rural developing country context, households with more educated mothers may engage in more compensatory behavior, targeting expenditure

[24] We assume the father is also above the median level of education, and thus the relevant coefficient is the sum of .110 and .118 as reported in Column (5) of Table 7.

to children with greater non-cognitive deficits, when compared to households with less educated mothers. Over time, this leads to greater persistence in non-cognitive challenges in households with less educated mothers, while children with more educated mothers show evidence of catch-up. Moreover, we can rule out that this pattern reflects simply higher socioeconomic status for households with more educated mothers, given that there is no evidence of heterogeneity with respect to income or assets. One suggestive hypothesis generated by our results is that more educated mothers may have other characteristics — different preferences, or greater bargaining power — that lead them to differentially invest in relatively weaker children.

There is an extensive literature that finds substantial intergenerational transmission linking maternal educational attainment and children's educational outcomes (Black et al., 2005b).[25] Our findings suggest that one potential channel for the intergenerational transmission of education may be the impact of maternal education on children's non-cognitive characteristics. These characteristics in turn affect their educational outcomes. This pattern also may have implications for interventions targeted to strengthen non-cognitive skills. Given that a number of evaluations have found that targeted early intervention can affect these skills, understanding how parents respond when allocating household resources may be a useful contribution to this policy debate.[26] If more educated mothers respond to such interventions by redirecting expenditure away from the child whose skills have been strengthened, this may be a mechanism that decreases the long-term benefits for the targeted child. There may, however, be positive spillovers for other siblings.

It is important to note that our sample is relatively small and drawn from only one province in China, and we should be cautious in concluding that the observed phenomenon is a general one. Gansu is one of the poorest regions of China; our sample is characterized by per capita income of only slightly over $200 in 2004, comparable to the poorer regions of sub-Saharan Africa. Accordingly, while this sample cannot plausibly be considered to be representative of higher-income areas of China, our results do suggest that compensatory behavior by parents may be found even in resource-constrained settings in the developing world. Thus the question of whether differential household responses to child variation in non-cognitive skills widen cross-household inequality in human capital over time may merit further analysis.

[25] See Björklund et al. (2011) for a review of this literature.

[26] The results from the Perry preschool study as reported in Schweinhart et al. (2005) are among the best known in this respect.

The authors declare they have no conflict of interest.

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6 Figures and Tables

Figure 1: Data structure

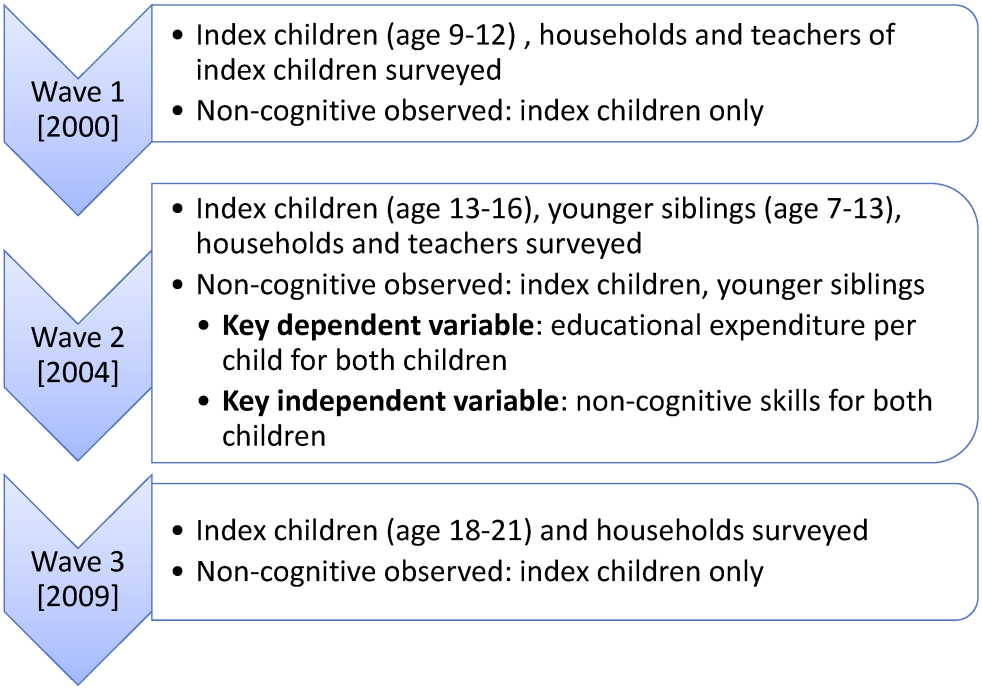
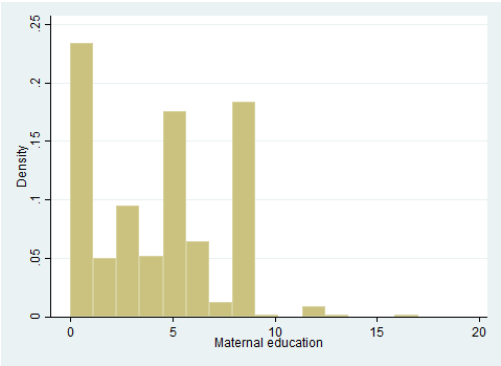


Figure 2: Parental education

(a) Maternal education



(b) Paternal education

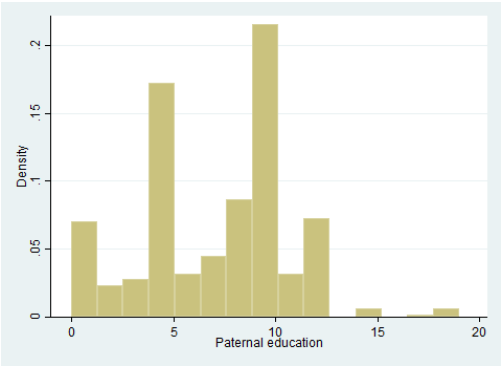
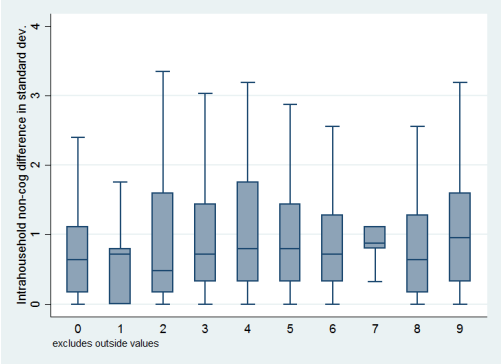
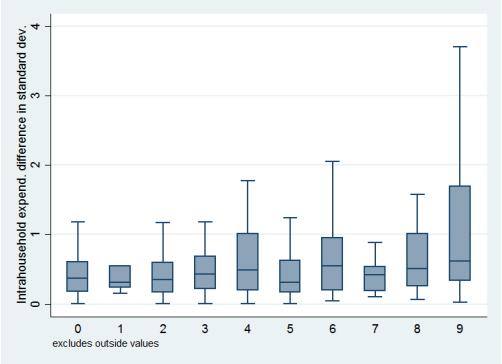


Figure 3: Intra-household differences in non-cognitive characteristics and expenditure, by mother's education

(a) Non-cognitive characteristics



(b) Expenditure



Notes: For each level of mother's education in years, the bottom bar corresponds to the minimum value of between-sibling absolute differences in non-cognitive characteristics (Figure 3a) or between-sibling absolute differences in normalized educational expenditure residuals (Figure 3b), while the top bar corresponds to the maximum value. The rectangle corresponds to the interquartile range, with the median value represented by the bold line bisecting the rectangle. Normalized expenditure residuals are calculated by regressing expenditure on child characteristics (gender, birth parity, cognitive skills, and height-for-age), generating the residuals and standardizing them to have mean zero and standard deviation one.

Table 1: Summary statistics

Panel A: Demographic data				Panel B: Educational expenditure per child			
	Sample	Subsample	p-value		Mean	Std. Dev.	Max.
Net income	6848.56	6534	.642	Discretionary	98.651	169.23	1660
Income per capita	1717.76	1583.68	.378	Tuition	165.667	159.21	2000
Mother education	4.31	4.25	.662	Supplies	36.434	38.29	300
Father education	7.12	7.01	.488	Transportation	11.553	39.03	500
Mother age	39.19	36.95	.000	Food	35.047	105.38	1200
Father age	42.57	38.89	.063	Tutoring	5.923	16.9	110
Index child age	15.09	14.99	.047	Other fees	9.695	28.09	360
Internalizing index	.01	-.01	.727				
Externalizing index	-.03	.02	.241				
Obs.	1918	408					

Notes: The sample encompasses the full sample of households that report income data; this is 1914 out of the full sample of 2000 households in the survey. The subsample is households with two-children families in which both children report data on non-cognitive characteristics as well as height-for-age. There are 408 households in the subsample of interest, and 816 children. Income is reported in yuan; internalizing and externalizing indices have been standardized to have means equal to zero and standard deviations equal to one, and a higher internalizing or externalizing index is indicative of fewer non-cognitive challenges. Column (3) reports the p-value for a test of equality of means across the sample and subsample. Educational expenditure is reported in yuan per semester for the subsample, and iscretionary expenditure is the sum of all expenditure categories excluding tuition.

Table 2: Non-cognitive characteristics and child characteristics

	Internal (1)	External (2)	Internal (3)	External (4)	Internal (5)	External (6)	Internal (7)	External (8)	Internal (9)	External (10)
Panel A: Child characteristics										
Sibling parity	-.005	-.124**							.173	.167
	(.059)	(.062)							(.142)	(.137)
Age			.013	.044**					.030	-.045
			(.018)	(.018)					(.048)	(.044)
Female					.030	.333***			.029	.305***
					(.076)	(.077)			(.081)	(.077)
Grade level							.018	.074***	.034	.143***
							(.020)	(.019)	(.038)	(.038)
Panel B: Cognitive skills and health										
Height-for-age	.043	.077**					.040	.078**		
	(.037)	(.036)					(.038)	(.037)		
Chinese Test Score			-.012**	-.007			-.008	-.003		
			(.005)	(.004)			(.005)	(.004)		
Math Test Score					-.009**	-.006	-.006	-.005		
					(.004)	(.004)	(.004)	(.004)		
Obs.	816	816	816	816	816	816	816	816	816	816

Notes: The dependent variables are the internalizing and externalizing indices. A higher internalizing or externalizing index is indicative of fewer non-cognitive challenges. The independent variable is the specified child characteristic, all measured in the second wave; all specifications include household fixed effects and standard errors clustered at the village level. Asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.

Table 3: Parental allocations and non-cognitive characteristics

	Discretionary				Tuition			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index	-13.085	-18.162**	-4.872	-8.450	1.883	-3.421	1.883	.457
	(8.738)	(8.536)	(7.388)	(7.217)	(5.282)	(4.708)	(5.282)	(5.674)
Chinese	104.656*		109.405*		44.109		44.109	
	(57.036)		(58.617)		(56.907)		(56.907)	
Mathematics	-24.517		-26.990		-13.950		-13.950	
	(27.985)		(28.204)		(26.820)		(26.820)	
Height-for-age	-1.198		-1.380		.911		.911	
	(6.002)		(6.164)		(4.627)		(4.627)	
Index employed	Int.		Ext.		Int.		Ext.	
Obs.	816	816	816	816	816	816	816	816
Mean (dep. var.)	98.651	98.651	98.651	98.651	165.667	165.667	165.667	165.667
St. dev. (dep. var.)	169.227	169.227	169.227	169.227	159.211	159.211	159.211	159.211

Notes: The dependent variables are discretionary educational expenditure and tuition expenditure per semester per child; discretionary expenditure is the sum of all categories of expenditure enumerated in Table 1 excluding tuition. The independent variable is the specified index of internalizing or externalizing behavior. A higher internalizing or externalizing index is indicative of fewer non-cognitive challenges. Specifications in Columns (1), (3) (5) and (7) include controls for sibling parity, gender, sibling gender, height-for-age and cognitive skills measured contemporaneously with non-cognitive characteristics, and a dummy for middle school; specifications reported in Columns (2), (4), (6) and (8) include only household fixed effects, year-of-birth fixed effects, and a dummy for middle school. Standard errors are clustered at the village level. Asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.

Table 4: Heterogeneous effects with respect to maternal education

	Discretionary				Tuition			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index	17.370**	15.464*	16.994**	15.835**	1.730	2.530	10.677	11.034
	(8.579)	(9.317)	(7.786)	(7.300)	(6.818)	(7.501)	(9.460)	(7.284)
Index x mother educ.	-7.477***	-8.003***	-6.419**	-6.600**	-.503	-1.416	-2.542	-2.874
	(2.720)	(2.687)	(2.831)	(2.628)	(1.672)	(1.593)	(2.923)	(2.636)
Chinese	126.580**		120.887**		64.620		65.689	
	(57.090)		(59.692)		(67.236)		(66.184)	
Chinese x mother educ.	-4.662*		-4.828*		-5.040		-4.980	
	(2.601)		(2.579)		(5.190)		(5.251)	
Mathematics	-21.877		-29.634		-22.024		-20.016	
	(28.282)		(29.196)		(29.521)		(29.046)	
Mathematics x mother educ.	1.729		2.050		3.423		3.405	
	(2.095)		(2.039)		(2.972)		(2.986)	
Height-for-age	-13.369		-13.865		3.705		3.169	
	(10.073)		(9.970)		(5.796)		(5.827)	
Height x mother educ.	2.284		2.417		-1.040		-.866	
	(2.097)		(2.169)		(1.403)		(1.397)	
Index employed	Int.		Ext.		Int.		Ext.	
Obs.	816	816	816	816	816	816	816	816
Mean (dep. var.)	98.651	98.651	98.651	98.651	165.667	165.667	165.667	165.667
St. dev. (dep. var.)	169.227	169.227	169.227	169.227	159.211	159.211	159.211	159.211

Notes: The dependent variables are educational expenditure per semester per child in the specified category; discretionary expenditure is the sum of all categories of expenditure enumerated in Table 1 excluding tuition. The independent variable is the specified index of internalizing or externalizing behavior, as well as the index interacted with maternal education in years. A higher internalizing or externalizing index is indicative of fewer non-cognitive challenges. Specifications in Columns (1), (3) (5) and (7) include controls for sibling parity, gender, sibling gender, height-for-age and cognitive skills measured contemporaneously with non-cognitive characteristics, interactions between all child characteristics and maternal education, year-of-birth and household fixed effects, and a dummy for middle school; specifications reported in Columns (2), (4), (6) and (8) include only household fixed effects, year-of-birth fixed effects, and a dummy for middle school. Standard errors are clustered at the village level. Asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.

Table 5: Heterogeneous effects with respect to paternal education

	Discretionary				Tuition			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index	-20.995	-22.975	-22.142	-26.877*	1.173	3.835	-.730	-3.738
	(18.886)	(18.797)	(16.236)	(15.941)	(9.048)	(8.006)	(12.002)	(15.707)
Index x father educ.	.080	.611	2.634	4.302**	-1.035	-1.106	.636	1.458
	(2.442)	(2.378)	(1.904)	(2.064)	(1.805)	(1.315)	(1.423)	(1.822)
Chinese	77.105		78.316		-30.902		-31.833	
	(62.541)		(63.498)		(75.737)		(79.008)	
Chinese x father educ.	1.079		.768		4.568		4.572	
	(2.690)		(2.588)		(5.535)		(5.479)	
Mathematics	-47.179		-50.321		-10.025		-11.849	
	(36.814)		(37.404)		(46.044)		(46.021)	
Mathematics x father educ.	2.823		2.457		-1.025		-1.112	
	(2.661)		(2.613)		(4.548)		(4.529)	
Height-for-age	6.814		8.260		13.342*		13.296*	
	(13.773)		(13.661)		(7.675)		(7.562)	
Height x father educ.	-1.473		-1.633		-1.747*		-1.749*	
		(1.753)		(2.357)		(1.174)		(1.493)
Index employed	Int.		Ext.		Int.		Ext.	
Obs.	806	806	806	806	806	806	806	806
Test $\beta_2^m = \beta_2^f$	.007	.012	.016	.012	.828	.854	.743	.378
Joint test	.006	.018	.022	.036	.259	.697	.478	.499
Mean (dep. var.)	98.651	98.651	98.651	98.651	165.667	165.667	165.667	165.667
St. dev. (dep. var.)	169.227	169.227	169.227	169.227	159.211	159.211	159.211	159.211

Notes: The dependent variables are educational expenditure per semester per child in the specified category; discretionary expenditure is the sum of all categories of expenditure enumerated in Table 1 excluding tuition. The independent variable is the specified index of internalizing or externalizing behavior, as well as the index interacted with paternal education in years. A higher internalizing or externalizing index is indicative of fewer non-cognitive challenges. Specifications in Columns (1), (3) (5) and (7) include controls for sibling parity, gender, sibling gender, height-for-age and cognitive skills measured contemporaneously with non-cognitive characteristics, interactions between all child characteristics and paternal education, year-of-birth and household fixed effects, and a dummy for middle school; specifications reported in Columns (2), (4), (6) and (8) include only household fixed effects, year-of-birth fixed effects, and a dummy for middle school. Standard errors are clustered at the village level. Asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.

Table 6: Robustness checks

	Discretionary				Tuition			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Alternate samples								
Index	15.627***	-7.788	22.104**	-25.495	6.936	9.656	7.926	.596
	(6.013)	(13.635)	(8.825)	(19.918)	(5.165)	(7.570)	(8.228)	(10.867)
Index x mother educ.	-5.406**		-8.943***		-2.086		-1.872	
	(2.307)		(3.171)		(1.708)		(2.240)	
Index x father educ.		.319		2.061		-1.584		.092
		(1.753)		(2.357)		(1.174)		(1.493)
Sample	Large sample		First-born sons		Large sample		First-born sons	
Obs.	1226	1210	816	806	1226	1210	816	806
Panel B: Alternate specifications								
Index	19.902**	.108	21.105	50.231**	8.023	-.021	7.171	16.233
	(9.447)	(.079)	(13.417)	(25.583)	(7.076)	(.073)	(15.580)	(21.645)
Index x mother educ.	-8.108**	-.034**	-12.009***	-21.080**	-1.494	.003	-.783	-3.319
	(3.212)	(.017)	(4.063)	(8.378)	(2.072)	(.013)	(3.928)	(6.363)
Specification	Grade FE	Log exp.	Percentile measure	Teacher report	Grade FE	Log exp.	Percentile measure	Teacher report
Obs.	816	816	786	816	816	816	786	816
Panel C: Endogeneity tests								
Index	3.798	22.169**	24.638***	19.629**	13.387	7.919	7.252	9.337
	(3.680)	(9.186)	(8.777)	(9.384)	(11.592)	(8.206)	(8.216)	(9.295)
Index x maternal educ.		-9.034***	-8.005***	-8.795***		-1.863	-2.122	-1.957
		(3.145)	(3.101)	(3.105)		(2.236)	(2.282)	(2.292)
Index x income			-1.364				.363	
			(.884)				(.576)	
Index x assets				-17.294				9.859
				(14.514)				(13.959)
Specification	Prim. measure	Lagged control	Income het.	Assets het.	Prim. measure	Lagged control	Income het.	Assets het.
Obs.	802	816	816	816	802	816	816	816
Mean (dep. var.)	98.651	98.651	98.651	98.651	165.667	165.667	165.667	165.667
St. dev. (dep. var.)	169.227	169.227	169.227	169.227	159.211	159.211	159.211	159.211

Notes: The dependent variables are educational expenditure per semester per child in the specified category; discretionary expenditure is the sum of all categories of expenditure enumerated in Table 1 excluding tuition. All specifications include the full set of control variables described in the notes to Tables 4 and 5. Standard errors are clustered at the village level.

In Panel A, the specification estimated in Columns (1)-(2) and Columns (5)-(6) include all families reporting data on two children. Specifications in Columns (3)-(4) and Columns (7)-(8) include only families reporting a first-born son. In Panel B, four robustness checks are reported. The main specification is re-estimated including grade fixed effects (Columns 1, 5); using log expenditure as the dependent variable (Columns 2, 6); converting the child non-cognitive measures to a percentile rank measure (Columns 3, 7); and using teacher reports of non-cognitive skills (Columns 4, 8).

In Panel C, four robustness checks exploring potential endogeneity in non-cognitive skills are reported. The main specification is re-estimated using wave one measures of non-cognitive skills (Columns 1, 5); controlling for lagged educational expenditure (Columns 2, 6); including additional interactions with household income (Columns 3, 7); and including additional interactions with a measure of household assets (Columns 4, 8). In all panels, asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.

Table 7: Persistence of non-cognitive skills in percentile and parental education

	Internal 2004		External 2004		Rosenberg 2009		Depression 2009	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Psychometric index 2000	.010	.070	-.004	.042				
	(.083)	(.060)	(.081)	(.060)				
Mother educ. 2000 int.	-.153*		-.105					
	(.088)		(.104)					
Father educ. 2000 int.	.160		.140					
	(.108)		(.108)					
Exp. 2000 int.		-.002***		-.0009*				
		(.0006)		(.0005)				
Psychometric index 2004					.108	.091	.129*	.162**
					(.069)	(.066)	(.073)	(.065)
Mother educ. 2004 int.					-.183*		-.0006	
					(.103)		(.096)	
Father educ. 2004 int.					.124		-.023	
					(.089)		(.102)	
Exp. 2004 int.						-2.24e-06		-.0004**
						(.0002)		(.0002)
Obs.	550	550	550	550	408	408	410	410

Notes: The dependent variables are the specified measure of non-cognitive skills from waves two and three, calculated in percentile terms. A higher index in internalizing or externalizing behavior is indicative of fewer non-cognitive challenges. A higher percentile in the Rosenberg index is associated with higher self-esteem. The depression index is inverted, and thus a higher percentile in the depression index is indicative of a lower level of depression. The independent variables include the psychometric index, the mean of internalizing and externalizing indices from waves one and two, calculated in percentile terms. The psychometric index is also interacted with dummy variables for the mother's (father's) education being above the median, and discretionary educational expenditure. All specifications include controls for cognitive skills measured in waves one and two, height-for-age, the parental education dummy variables, net income, assets, and fixed capital in the household, the number of siblings, sibling gender, and sibling gender interacted with the number of siblings, and county and year-of-birth fixed effects; the specifications including an interaction effect with expenditure also include linear and quadratic terms for total and discretionary educational expenditure, and a dummy for discretionary expenditure above the median. Standard errors are clustered at the level of the village. Asterisks indicate significant at the 5, 1 and .1 percent levels; daggers indicate significance at the 10 percent level.