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Family Background, Ability and Student Achievement in Rural China –Identifying the Effects of Unobservable Ability Using Famine-Generated Instruments

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Keywords

student achievement, ability, Famine in China 1958-1961

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This paper investigates the effects of family background on academic achievement in basic education (grade 1-9) in rural China, using information on a sample of children aged 9-12 in 2000 from Gansu, China. The instrumental variable method developed by Mason and Griliches (1972), and Blackburn and Neumark (1992) is applied to control for unobserved child ability. Scores of a cognitive ability tests are first used to proxy unobservable child innate ability. This error-ridden measure of child innate ability is then instrumented by an instrumental variable generated by the Great Famine in China, 1958-1961. Empirical results indicate that omission of child innate ability leads to overestimation of income effects. Parental education is found to be key determinants of student achievement, but the roles of father's education and mother's education differ across child gender and levels of ability. For example, father's education has significantly positive effect on academic achievements for both boys and girls, while mother's education only matters for girls. The effect of father's education matters for lower ability children, while mother's education matters for higher ability children.

1. Introduction

Education is widely seen as a key determinant of continuous and stable income growth in developing countries (e.g., Duflo 2001). In the case of rural China, evidence suggests that education has contributed to income growth in a number of ways during China's transition from a planned economy to a market economy since the early 1980s.[1] Although less studied than the quantity of education (i.e., years of schooling), the quality of education or acquired academic skills, as measured by achievement test scores, has also been shown to contribute to household income in developing countries (see e.g., Glewwe 1996; Jollife 1998).[2] In China, one particular way academic skills contribute to income is through their impacts on years of schooling, because admission into high schools (grades 10-12) is based solely on students' scores of their high school entrance exams. Only students with adequate academic skills can score high enough to enter high school and later enjoy higher returns to high school education[3] in the labor markets than their fellow students who fail the entrance exams. Unfortunately, despite the importance of academic skills to boost future rural income growth and the commitment of China's government to continue to alleviate rural poverty, few studies have focused on investigating the determinants of academic skills or student achievement in rural China.

This first goal of this paper is to fill this gap by examining the determinants of child academic skills in rural China. Three sets of variables are often included as the determinants of

[1] Education has raised farmers' incomes by enhancing their managerial skills and labor productivity in agricultural production (Yang 1997a). More importantly, when restrictions on factor markets and non-farm economic activities were loosened during the transition, rural households with better-educated members acted more quickly in reallocating capital and labor to non-farm activities (e.g., food processing), capturing higher returns yielded by these activities (Yang 2004). Moreover, better-educated people have better access to and tend to specialize in non-farm and better-paid occupations (Yang 1997b). In particular, people who completed high school education are more likely to participate in non-farm employment than people with lower levels of education (Zhao 1997).

[2] For example, mathematics and English skills have positive effects on household income in Ghana (Jollife 1998).

[3] In a recent paper, de Brauw and Rozelle (2008) find that the returns to high school education exceed the returns to primary and low-secondary education in rural China.

student achievement in the literature: family background variables such as household income and parental education; school quality variables such as teacher experience and physical facilities; and child characteristics such as gender, age, and ability (see e.g., Haveman and Wolfe 1995). The most common findings are the statistically significant effects of family background variables (Behrman and Knowles 1999) and the statistically insignificant effects of school quality variables (Hanushek 2003 and Glewwe 2002). The strong associations between family background and child achievements are well documented. For example, the marginal benefits from investing in child education may be positively correlated with household income, because richer parents can afford educational inputs of higher quality (Behrman and Knowles 1999). Also, better-educated parents might place high values on child education and be more capable and also more willing to help their children. The findings of strong family background effects and insignificant school quality effects suggest that the focus of academic research and governmental intervention programs in developing countries might be put on the family side.

In the case of rural China, one would also expect family background variables to play important roles in determining achievement of children. This is because the rural families have long been responsible for funding rural children's education, as a consequence of China's education reform. Since the middle 1980s, the decentralization of the financial structure of China's basic education has shifted the financial responsibilities for funding basic education from the central government to local governments and rural communities. Local communities, in turn, have being raising funds for schools by charging rural household considerable tuition and numerous fees (Tsang 1996). Because most rural households do not have easy access to credit, household income is the major resource rural parents have to pay for school education and other educational inputs. Furthermore, the effects of family background have been found to be different across child gender in China (Brown and Park 2002). Thus, the focus of the first goal of this paper is on examining the effects of family background variables and their interactions with child characteristics.

The second goal of this paper is to overcome some persistent problems in empirical analysis while pursuing the first goal. The empirical studies using retrospective data often suffers from estimation problems such as omitted variable bias and measurement error bias (Glewwe 2002). For example, the omission of child innate ability could bias the estimates of the effects of household income and parental education. This is because children's innate ability and parental ability are genetically interlinked and thus children's innate ability is also possibly correlated with parental education or household income; the later two are obviously determined by parental ability. Even though some measures of innate ability are available, they are at best imperfect proxies in that they often have a certain amount of measurement error. This paper makes its main contribution by developing an instrumental variable (IV) procedure to control for unobserved innate ability. To explore exogenous variation in child ability, a "natural experiment" generated by the famine in China, 1958-1961, is used to create an instrument variable for an error-ridden measurement of innate ability. The famine-generated IV procedure helps identify the effect of unobservable ability and hence estimate family background effects more consistently.

Another source of bias comes from the school side. One explanation of school characteristics being statistically insignificant is the bias caused by the possible omission of school variables (Glewwe and Kremer 2006). Unobserved school quality may not only bias estimates of the effects of the observed school quality variables that are included in the regression, but also lead to bias estimates of the effects of family background variables if parents' decision depend on unmeasured school quality such as reputation. Thus, empirical methods to control for school quality are needed even when on focuses on the effects of family background on student achievement. This paper applies school fixed effects method to control for effects of school quality variables, both observed and unobserved.

The rest of the paper proceeds as follows. The next section lays out the conceptual framework that is used to analyze the determinants of academic skills. Section 3 discusses potential identification issues that may affect our empirical estimation. Section 4 develops the strategies to resolve the identification issues. Section 5 describes the data. Section 6 reports empirical findings. The final section concludes.

2. Estimation Framework

There are more than one relationship between family background and student achievement that are of interests in empirical research. For example, this relationship could be an input-output relation in which family background such as parental education affect directly the student achievement in the production process. Or, this relationship could be a demand relation in which family background variables also affect student achievement through their impacts on educational inputs. This section sketches a simple framework for thinking about the relationship(s) between family background and student achievement, and the empirical specification that serves as the estimating equation of empirical analysis.

Many empirical studies have tried to estimate an education production function of student achievement:

$$\text{(1)} \qquad \mathrm{H} = \mathrm{H}_P\ (\mathbf{I};\ \mathbf{k}, \mathbf{f}, \mathbf{q}),$$

where H stands for child academic skills (*human capital*), as measured by achievement test scores. The subscript P denotes H_P as a production relation. The vector **I** is a set of educational investment, which includes years of schooling and other educational inputs, such as textbooks, extra reading materials and tutoring services. The vector **k** is a set of child (*kid*) characteristics, including gender, age and innate ability (denoted A). The vector **f** is a set of family background characteristics, most important of which are household income and parental education. The vector **q** represents school quality including teacher experience, the quantity/quality of the physical facilities and other aspects such as school reputation. $H_P(\cdot)$ is assumed to satisfy the basic properties of a production function, e.g. concavity and differentiability. Note that all variables in the vector **I** are direct inputs that can be chosen by parents, while all variables in **k**, **f** and **q** are exogenously given.[4] These exogenous variables allow for heterogeneity in the production technology used to produce student achievement across families and schools.

If all variables in **I**, **k**, **f** and **q** are observed and available in the data, one can consistently estimate equation (1), the production function, using ordinary least-squares (OLS) regression. Coefficients on these variables measure the *direct* effects of these variables. However, no survey can collect information on all these variables, and there is always possibility of omitted variables bias. Instead, by solving the household optimization problem, one can estimate a *demand* relation between student achievement and family background.

Suppose a household maximizes the following (quasi-concave) utility function:

$$(2) \qquad \underset{C,\,\mathbf{I}}{\text{Max}}\; U = U(C, H),$$

where C is the composite household consumption good. The household faces two constraints in the maximization process: the budget constraint and the technology constraint. The household budget constraint is defined as:

$$(3) \qquad C + \sum_j p_j I_j = m,$$

where I_j is the j-th element of the educational input vector, $\mathbf{I}$, p_j is the corresponding j-th element in the price vector, $\mathbf{p}$, and m is the total amount of monetary resources available to the household. The technology constraint is defined by equation (1).

Solving problem (2) subject to constraints (1) and (3) yields the following demand functions:

$$(4) \qquad C = C(\mathbf{p}, m; \mathbf{k}, \mathbf{f}, \mathbf{q}),$$

$$(5) \qquad I_j = I_j(\mathbf{p}, m; \mathbf{k}, \mathbf{f}, \mathbf{q}).$$

where equation (4) is the demand function for household consumption, and equation (5) is the demand function for the j-th educational input.[5] Substituting (5) into equation (3), we obtain the demand function for child achievement:

$$(6a) \qquad H = H_P(\mathbf{I}(\mathbf{p}, m; \mathbf{k}, \mathbf{f}, \mathbf{q})); \mathbf{k}, \mathbf{f}, \mathbf{q}).$$

Because elements in $\mathbf{I}$ are functions of the same set of exogenous variables, ($\mathbf{k}$, $\mathbf{f}$, $\mathbf{q}$), equation (6a) can be expressed as the following equation:

$$(6b) \qquad H = H_D(\mathbf{p}, m; \mathbf{k}, \mathbf{f}, \mathbf{q}).$$

Since equation (6b) expresses H as a function of only exogenous variables, it is a *reduced-form* demand equation (as opposed to the *structural* relationship in equation (1)). The subscript D denotes H_D as a demand function. The reduced-form demand function is attractive for two reasons. First, from the above derivation, one can see that the reduced-form relationship characterized in equation (6b) takes into account the *behavioral* adjustments (through the optimization process) to $\mathbf{I}$ in response to exogenous changes in any exogenous variable in ($\mathbf{p}$, m,

[5] A set of equation (5) has been estimated by Brown (2006) using the same data set used in this paper.

k, **f, q**), while holding others constant. To the extent that many governmental intervention programs will lead to behavioral adjustments, equation (6b) is probably the most relevant for policy makers (Blau 1999). Second, the data requirement for estimating a reduced-form demand function is much less demanding for estimating a production function. Because all inputs **I** have been substituted out, and thus the estimation is less likely to suffer from omitted variable bias. Thus, equation (6b) is the key relationship of interest in this paper.

A simple linear approximation of equation (6b) can be written as:

$$(7) \qquad H = \mathbf{x}\boldsymbol{\beta} + \mathbf{q}\boldsymbol{\eta} + \alpha A + \varepsilon ,$$

where $\mathbf{x} = (\mathbf{p}, \mathrm{m}; \mathbf{k}, \mathbf{f})$ is the matrix of all exogenous variables (except for ability A). A is child ability and **q** is the vector of school quality. They are listed separately from **x** because they are the sources of potential biases in estimation that will be discussed in more details in section 3 below. and ε is the error term that includes factors that have predictive power of H but are not collected in data. One important example relevant to this paper is the measurement errors in A and x variables. Equation (7) is the statistical model for the demand for student achievement that will be estimated below. If equation (7) is a good approximation of equation (6b), and if we have all data on variables on the right hand side of equation (7), we can consistently estimate the effects of the right hand side variables in equation (7).

3. Identification Issues

Even when estimating a reduced form equation such as equation (7), careful econometric analysis would be needed in order to consistently estimate the effects of the exogenous variables.

This section discusses identification issues that are raised by potential omitted variables and measurement error. The next section presents our strategies to tackle these identification issues.

Unobserved school quality. Although they are often treated as inputs in education production, school quality variables (**q**) cannot be substituted out in equation (6b) because they are not choice variable for parents. Many empirical studies attempt to assess the effects of school quality on student achievement, or simply to control for them, by including a list of school characteristics that measure some dimensions of school quality. However, many dimensions of school quality could affect student achievement. Hence it is likely that in most studies there are always some school quality variables that are omitted, often because they are unobserved. By comparing prospective estimates and retrospective estimates using data in Kenya, Glewwe et al (2004) find evidence of omitted school quality variables bias, even when controlling for other observed school quality variables.

The failure of controlling for omitted school quality variables will not only bias the estimated effects of observed school quality variables, but could also lead to biased estimates of the effects of variables in **x**. This is especially possible in the rural China case, given the decentralization of funding structure of the basic education sector in rural areas. Schools in more wealthy areas are probably of better qualities because local communities (consist of wealthy households) in more wealthy areas probably have more capacity to invest in schools. Since household income may be correlated with school quality, the omission of variables that measure school quality may also bias the coefficient on variables that measure household income.

Unobserved Child Ability. Child innate ability can never be perfectly observed. The omission of child innate ability could lead to upward biases on the estimated impacts of family background characteristics (see e.g., Behrman and Rosenzweig 1999, among others). The omitted variable bias arises because child innate ability A and family background **f** are often correlated. For example, A is positively correlated with **f** through the genetic link between child ability and parental ability and the effect of parental ability on **f**.

Measurement error in Ability measures. In attempts to control for unobserved child ability, many studies have used some measures of the innate ability, most often intelligence test scores, to proxy the true innate ability. For example, Kingdon (1996) used Raven's Coloured Progressive Matrices test score as a proxy of innate ability and replaced *A* directly with the Raven's score in the regression. However, none of the currently available measurements can perfectly measure the true innate ability. In fact, any ability measures might reflect the influence of environmental factors (American Psychological Association 1995). In other words, these ability measures are at best imperfect proxies for the true innate ability. Although the use of the imperfect proxies can, to some extent, reduce omitted variable bias, it will probably lead to additional problems because they are error-ridden and the inclusion of them may contaminate the estimates on other explanatory variables. This paper uses a cognitive development measure score (CDM; see the data section below for a description) to measure child innate ability, and it will also likely to have measurement error problems that need to be appropriately dealt with.

Suppose CMD measures the true ability A with measurement error e, as follows:

$$\text{(8)} \qquad \mathrm{CDM} = \mathrm{A} + \mathrm{e}.$$

Simple algebra yields $\mathrm{A} = \mathrm{CDM} - \mathrm{e}$. Thus, using CDM as a proxy for A, the actual equation being estimated is

$$\text{(7a)} \qquad \begin{aligned} \mathrm{H} &= \mathbf{x\beta} + \mathbf{q\eta} + \alpha \mathrm{A} + \varepsilon \\ &= \mathbf{x\beta} + \mathbf{q\eta} + \alpha \cdot \mathrm{CMD} - \alpha \cdot \mathrm{e} + \varepsilon \end{aligned}.$$

Whether measurement error e will cause problems in estimation depends on the correlation between CDM and e (Wooldridge 2002). If e is correlated with the true ability A but not its measure CDM, OLS will produce consistent (but not efficient) estimates of all the coefficients in (7a). But if e is correlated with CMD, but the true ability, the existence of e will likely cause bias in estimates of *all* coefficients. Unfortunately, in the context of this paper, e is very likely to be correlated with CMD, i.e. Cov (CDM, e) $\neq$ 0. This leads us to the classical error-in-variable (CEV) case. By standard econometric theory, in the CEV case, the ordinary least squares regression of H on **x**, CMD and **q** generally gives inconsistent estimates of *all* coefficients (Wooldridge 2002).[6]

4. Identification Strategy

4.1. The fixed-effects-instrumental-variable approach (FE-IV)

Since the focus of this paper in on the family side, a simple method to control for unobserved school quality is simply to use the fixed effects estimator at school levels. Take equation (7) for example, for the *i*-th student in the *k*-th school, the achievement demand function can be rewritten as,

$$
\begin{aligned}
\text{(7b)} \qquad \mathrm{H}_{ik} &= \mathbf{x}_{ik}\boldsymbol{\beta} + \mathbf{q}_k\boldsymbol{\eta} + \alpha \mathrm{A}_{ik} + \varepsilon_{ik} \\
&= \mathbf{x}_{ik}\boldsymbol{\beta} + \mathrm{SC}_k + \alpha \mathrm{A}_{ik} + \varepsilon_{ik}
\end{aligned}
$$

The vector of school quality, $\mathbf{q}_k$, are constant across all students in school *k*. The entire set of $\mathbf{q}_k$, together with its coefficient vector $\boldsymbol{\eta}$, can be pooled into a school-specific constant, SC_k (= $\mathbf{q}_k\boldsymbol{\eta}$). Then, the usual fixed effects estimation procedure applies. The fixed effect estimator is attractive because it allows **x** to be correlated with unobserved **q** variables since the latter are included in the regression through SC_k. Note that the term SC_k captures the effects of all school level characteristics that do not vary within school *k*, both observed and unobserved.

One still needs to control for the unobserved child ability A_{ik} in equation (7b) above, even when unobserved school quality have been controlled for using school fixed effects. Since this paper uses CDM to proxy the unobserved innate ability, the identification issues caused by imperfect proxy for child ability discussed in the above section must be addressed here. Our approach is to treat CDM as an *indicator*, instead of a proxy variable, of the true innate ability, and then apply standard IV procedures to this indicator.[7] This IV approach is proposed by Griliches and Mason (1972) and also applied in Blackburn and Neumark (1992).

With school fixed effects being controlled, equation (7a) becomes:

$$\text{(7c)}\quad \mathrm{H}_{ik} = \mathbf{x}_{ik}\boldsymbol{\beta} + \mathrm{SC}_k + \alpha\,\mathrm{CDM}_{ik} - \alpha\,\mathrm{e}_{ik} + \varepsilon_{ik}$$

With unobserved school quality being controlled for, consistent estimates of the effects of **x** variables can then be obtained if valid instrumental variables are available for CDM_{ik}. The set of suitable IV used in this paper is described in the next subsection.

4.2. Famine in China, 1958-1961 and the Famine-Generated IVs

The Famine. Instrumental variables are usually difficult to find. But history helps. A natural experiment generated by the Great Famine in China, 1958-1961, provides candidates for the IV needed. The famine resulted from the agricultural crisis in 1958 and the following political decisions regarding food allocation.[8] The national grain production plunged by 15

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possible approach can be found in the Ghana study by Glewwe and Jacoby (1994). The authors extracted an innate ability factor as a *household fixed effect,* using parental ability measures. In other words, the *IQ* score variable, i.e. the Raven score of the child, is instrumented by using father and mother's Raven's scores and other exogenous variables. Note that this approach is valid only if measurement errors in parental ability and child ability are uncorrelated. Also, because parental ability measures are not available in the data set used in this paper, other possibly suitable IVs are needed.

[7] Detailed analysis of the causes of this famine can be found in Lin (1990), Lin and Yang (1998), Lin and Yang (2000), among others.

[8] Indeed, Lin and Yang (2000) argue that food entitlement might be the fundamental cause of the famine.

percent in 1959 from its peak of 200 million tons in 1958. It declined by another 15 percent in 1960 and stayed flat in 1961 (State Statistical Bureau 1991). In order to deal with the food shortage caused by the sharply decreased agricultural output, food allocation policies were established during this period that gave urban grain supplies higher priority over rural localities. To guarantee the success of the Great Leap Forward in 1958, Chairman Mao's 'One Chessboard' speech in the spring of 1959 reaffirmed the urban-biased food allocation policy. This exacerbated the shock of original output decline in the rural area (Lin and Yang 2000).[9] .

The famine in 1958-1961 is now recognized as the worst in human history. It has been estimated that the famine caused deaths of some 30 million of people and lost births of more than 30 million, mostly in rural areas (Ashton et al. 1984). Gansu province, the study area in this paper, was seriously affected by the famine and the urban-biased policies that followed. The administration extracted 361 thousand tons of grain from Gansu to support the urban food supply between 1959 and 1960 despite the food shortage in the province (Walker 1984). At the same time, the rigorously implemented residence registration (*Hukou*) system prevented rural residents from migrating to urban areas where food shortage was not as dire. As a consequence, death rates increased dramatically in Gansu from 11.1 ‰ in 1957 to 21.1‰ in 1958 and then peaked at 41.3 ‰ in 1960. The death rate in Gansu in 1958 was the third highest among all 28 provinces for which data were available.

The Famine-Generated IV. It is clear that the famine cohort, people who were born during or slightly before the famine period (i.e. people who spent their early childhoods during the famine) and survived could be a very different cohort from the rest of the population in Gansu. In particular, people in the famine cohort might have higher ability endowment than those who did not survive and those who were born long after or long before the famine because the famine "selected" out people with higher ability.[10]

In addition to the selection effect, the famine can also have a somewhat offset effect on parents' ability through poor prenatal nutrition intake. Recent studies on the long-term impacts of the famine (e.g., Chen et al. 2007) indicates that people born during the famine period have significantly lower heights than they would otherwise have had, which implies low nutrition intakes during the famine. Early prenatal nutrition has been found to be essential in human brain development. For example, Villar et al. (1984) found that infants whose head growth slowed due to poor prenatal nutrition before 26 weeks of gestation (as measured by ultrasound) grew slower than otherwise, and scored lower in mental performance in preschool years. Similarly, one would expect the famine-born cohort to have lower ability than they would otherwise. This nutrition effect could offset the selection effect the famine has on ability.

If a subset of the parents of the sample children belongs to the famine cohort, then famine can serve as an IV for three reasons. First, there is a large literature showing that parents' innate ability is closely correlated with their children's innate ability. Second, since the famine affects parents' ability, either through the selection effect or through the poor prenatal nutrition effect, the famine is likely to be correlated with children's ability. Third, because the famine can be treated as a natural experiment, the variation in children's innate ability that is associated with the famine is exogenous and uncorrelated with the error term. Therefore, the famine can serve as an instrumental variable for children's innate ability. We create the instrumental variable using

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that there is no contradiction between this argument and that in Chen et al. (2007). Famine could not only select out people with high endowment, but also affect their lives badly ever since. The idea here is that, their high endowment could have been masked by the long term negative impact of famine. Such endowment could still be transmitted to their children, however.

[10]Due to reasons such as migration out of Gansu province and child death, the total number of sampled children interviewed in 2004 is 1912.

parents' birth year information: the total number of parents that were born and then survived their early childhood during the famine.

5. Data

The data used in this paper come from the Gansu Survey of Children and Families (GSCF). The survey follows 2000 sample children[11] over years (2000, 2004 and 2007) in Gansu, a poor province located in northwestern China. During the 2000 survey, a stratified sampling strategy was first used to select 20 counties from all non-urban, non-Tibetan counties in the province. Within each of the 20 counties, 5 villages were then selected. Within each of the 100 sample villages, 20 children were then randomly selected from the full cohort of nine to twelve year-old children. Separate questionnaires were administered to the sample children, their parents, local village leaders as well as to teachers and principals of the schools the sample children enrolled in at the time of the survey.

Since the focus of this paper is academic achievement in basic education, a sub-sample of children who were enrolled in grades 1-9 (excluding high school students in 2004) is used. One reason is that basic education is compulsory while high school education is voluntary. Many aspects of high school education, e.g., curriculum, cost[12] and funding structure[13] and motivation

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hina, high school tuition is not free, while in many areas basic education is claimed to be free of tuition.

[12] High schools in China are funded by county governments, while primary schools and middle schools are funded by township governments and local communities.

[13] See Zhao and Glewwe (forthcoming) for an analysis of the determinants of the dropout decisions of these children.

of teachers and students, are different from that of basic education. In fact, about 250 children in this sample have dropped out of school before they reach high school education.[14]

The dependent variable, child academic skill, is measured by math test scores. In 2004, a math test was administrated to all sampled children. The tests were designed by experts at the Gansu Educational Commission to cover the range of official primary school curriculum. To ensure that the tests assessed an appropriate range of knowledge given the child's education, separate exams were given to children in different grades. Those sample children that were interviewed in 2000 but dropped out before 2004 also took the tests in 2004. Tests that were equivalent to the highest grade they have ever attained were given to them. The test scores are then adjusted to be comparable. The inclusion of these children eliminates sample selection biases caused by dropping out of school. Note that for the children who have dropped out of schools, there will not be any information school available in the 2004 panel.[15] Our strategy is to replace school codes by the village codes for these children in our data. This strategy can control for school fixed effect well because each village in rural Gansu usually have one primary school and one lower-secondary school, and China's policy on basic education enrollment is based on locality of residence.

The most important family background variables are household income and parental education. In household surveys, measures of household income are often collected by asking respondents to report sources and amounts of income, which is subject to measurement error caused by reporting error (Deaton 1997). Household expenditure would be a better measurement of household income. However, since measurements of household expenditure often come from

her possible way is to replace school codes in 2004 by school codes in 2000. But one caveat of this approach is that many dropped out children have finished middle school education, which means the schools they attended in 2000 were their primary schools.

[15] Inde

respondents' recalling of expenses, they are also susceptible to measurement error unless respondents keep a diary of daily consumption. To deal with measurement error in expenditure data, the log value of durables per capita in 2000 is used as an instrumental variable. During the survey, the enumerators conducted the interviews in the household residence calculated the value of durables, and thus the measurement error in the value of durable is unlikely to be correlated with the measurement error in household expenditure reported by household members. Additionally, since educational investment is a medium or long term (probably 5-10 years) decision, it is probably better explained by long term household resources instead of current yearly household resources. Using the value of household durables in 2000 as an instrument for household expenditure is similar to exacting a long term wealth component from the current household resource measure. In most of the regressions below, household expenditure is instrumented by the value of durables in 2000.

Parental education has been the focus in many empirical studies on child human capital outcomes. In addition to ask the highest degree completed by the parents in most household surveys in China, how many years were spent in pursuing the highest degree was collected. For example, many parents spent two years, instead of three years, in middle schools, due to the education policy in the 1970s. Hence, the years of schooling calculated in this sample will be more precise than in most household surveys in China.

Child characteristics include gender and child age measured in month. Squared age is also added in order to capture the nonlinear effect of age on academic skills. More importantly, we also include child ability. A cognitive development test was administrated to each sample child in 2000 when they aged 9 to 12. Scores of this cognitive test is used to measure child innate ability.

Table 1 summarizes definitions and summary statistics of variables used in the empirical analysis.

6 Empirical Results

6.1. Potential bias: Omitted ability variable vs. Measurement error in CDM score.

Table 2 summarizes the empirical results for estimating a variety of equation (7), the reduced form demand function for math achievement. At the same time, comparison across specifications facilitates the investigation of potential bias caused by either the omitted innate ability or measurement error contained in the ability measure CDM. Since this paper makes no attempt to estimate the effect of school quality variables on math achievement, all specifications in table 2 control for school fixed effects. The main message in this sub-section is that although adding an ability measure as a proxy for child ability reduces omitted ability bias to some extent, measurement error in the ability measure causes new problems.

The first half of table 2 (column 1-2) does not control for child ability. The only difference between these two specifications is that household expenditure in the second (column 2) is instrumented by the log value of durables in 2000, while in the first specification (column 1) it is treated as exogenous, i.e., not containing any measurement error. The comparison of the estimation results in these two specifications indicates the need to instrument household expenditure. [16] Thus, in all other specifications (column 2-4), per capita household expenditure is instrumented by the log value of durables per capita in 2000.

The second half of table 2, columns (3) and (4), controls for child innate ability, but with different methods. The specification in column (3) uses CDM score as a proxy variable for ability A and directly replaces A in the regression. In the last specification (column 4), the CDM score is instrumented by the IV generated by the famine that indicates the number of birth parents who were born and then survived the famine.[17]

The following analysis investigates the potential bias by comparing the coefficient estimates from the baseline regression column (2) with those from column (3) and (4). Consistent with the finding in Behrman and Rosenzweig (1999), among others, the omission of child innate ability leads to upward ability-bias on the estimated impact of family income. For example, the comparison of column (2) and column (4) indicates that household income effect is overestimated. The coefficient estimate on the log value of expenditure per capita in column (1) is 3 points higher than the consistent estimate in column (4). Interestingly, the effect of father's education is underestimated (by about one third of the size of the consistent estimate in column (4)) in column (2). This suggests that there might be some interaction effects between child ability and family background variables, which will be discussed below.

In attempts to remove omitted ability bias from omitting ability, CDM score is used to proxy ability in the specification in column (3). The results clearly suggest that CDM score is likely to measure ability A with a substantial amount of error. First and mostly significantly, the results clearly indicate the existence of attenuation bias in the coefficient estimate on A when it is proxied by CDM score. Compared to the result from the column (4), where CDM score is instrumented by the famine-generated IV, the magnitude of the estimate in column (3) is less than one third of size of the consistent estimate in column (4).

In summary, by comparing results from estimating different specifications that differ in the approaches to deal with estimation problems, we show the biases could arise if one does not

[17]The significant predictive power of IV on the endogenous variables in the first-stage regressions (column 1 and 2 in Table 3) indicate the validity of our IV. In particular, the F-statistic of the famine-IV is close to 10, the rule of thumb for valid instrument variables.

control for child ability. In addition, if ability is not appropriately controlled for, problems persist. Even if an ability measure, e.g., CDM score in this paper, is available, replacing A with CDM score directly might cause other biases if CDM score contains a certain amount of error.

6.2. The main effects of family background and child characteristics

As expected, family background and child characteristics play important roles on student math achievement (Table 2, column 4). However, not all their roles are consistent to common findings in the literature. One striking finding from comparing income effects in column (2) and (4) is that strong household income effects found in previous literature might be simply reflecting the effects of child innate ability. Strong positive income effect is found in column (2) where child innate ability is left in the error term. Since household expenditure is in log scale, a ten percent increase in household expenditure is associated with 0.4 points increase in math achievement, which is lager than the effects of increasing father's education by one year. But when child innate ability is appropriately controlled for in column (4), income effect drops greatly and becomes insignificant at any conventional level. Meanwhile, a strong effect of innate ability on math achievement is found. Also, even when an ability measure is used to proxy unobserved child ability (column 3), income effect is still overestimated: although the income effect decreased somewhat when CDM is added in column (3), it is still significant at 10% level.

The second interesting finding is that the most significant family background variable is father's education, but not mother's education which has long been found to be a more significant determinant than father's education on many measures of child human capital outcomes in the literature. In fact, mother's education plays almost no role in child math achievement (table 2, column 2-4) in the linear specifications of equation (7).

6.3. Interaction effects: Gender and Family Background

The above findings are plausible only when the specification in equation (7) is correct. Table 4 explores more possibilities by introducing interaction terms between family background variables and child characteristics. This sub-section considers the interaction between family background and child gender, which is suggested by Brown and Park (2002)'s findings on gender effect in China. Household expenditure and parental education are interacted with the gender dummy. [18] No significant income effect or its interaction effect with child gender is found. The interaction between father's education and child gender are also never significant. Thus, only the interaction between mother's education and child gender is kept in the regression reported in table 4.

The main finding is that although both father's education and mother's education have significant impacts on child math achievement, the effects of father's education and mother's education differ. Other things being equal, an additional year of father's education is associated with about 0.4 point increase in math achievement, for both boys and girls. In contrast, mother's education matters only for girls, and the effect of mother's education is slightly higher than that of father's education.

As has been commonly documented in research on developing countries, gender gap is also found in table 4 when interaction effects are considered. First, girls scored lower than boys if their mothers' years of schooling are lower than 4.3 years, which is higher than the mean level of mothers' education (i.e., four years; see table 1) in this sample.[19] Second, mother's education

[18] The interaction between household expenditure and child gender is instrumented by the interaction between the value of durable in 2000 and child gender.

[19] The marginal effect of being a girl is $-1.89 + 0.43\times$ mother's education. So if mother's education is more than 4.3 years, the marginal effect of being a girl is positive.

plays an important role in raising girls' math achievement but not in raising boys. Along with these two findings, the fact that more than 500 mothers in the sample have never been to school suggests that females may have been discriminated against in education for more than one generation. Given that family background, school quality and child ability have been controlled for, one possible explanation for the differential effects of mother's education on boys' and girls' math achievement is that more-educated mother might provide a household role model for girls. In other words, more-educated mothers provide high motivation for their daughters, who would be discriminated against otherwise, to study hard.

6.4 Interaction Effects: Ability and Family Background

Strong ability effect on math achievement has been found above (table 2, column 4; table 4, column 1): Children who with the ability to score one point higher in CDM than average will score 1 point higher in math achievement, other ting being equal. However, this finding is not helpful in providing evidence for government to design intervention programs.[20] Therefore, it might be more useful to investigate the interaction effects between child ability[21] and family background variables. The results are summarized in table 4, column 2.[22]

Again, no income effect (or its interaction effects with child characteristics) is found. Also, the three way interaction, child gender-ability-family background has little predictive power on student math achievement. Importantly, differential effects of parental education are again found across innate ability levels. For example, the effect of father's education decreases

[20] It is helpful in the sense that it suggests the strong household income effect might be picking up the ability effect.
[21] The fitted value from the first-stage regression of CDM in table 3 is used as the proxy for child ability.
[22] The interaction between household expenditure and child ability and the three way interaction among household expenditure, child gender and child ability are not significant and are thus dropped from the regression.

as child ability increases. In other words, the effect of father's education is higher for a child with lower innate ability than a child with higher innate ability. On the contrary, the effect of mother's education has higher an impact for children with higher ability. These suggest different educational investment strategies adapted by fathers and mothers. While fathers might adapt compensating strategy, i.e., invest more in less able children, mothers do the opposite. Although the arguments that fathers and mothers adapt different strategy seems strange, they do not lack of empirical support. For example, for the same sample of children, Brown (2006) finds that father's education has a significantly negative effect on the amount of extra reading material purchased for children with higher ability, while mother's education has a small positive impact.[23] This pattern reverses in the number of times parents discuss their children's performance in school with their school teachers. These findings, i.e., the differential effects of father's and mother's education across child gender and ability level, suggest the need for further research on household structure in rural China.

7. Summary and Conclusions

This paper investigates the determinants of academic skills (as measured by math test scores) acquired in basic education (i.e. grades 1-9) for a sample of rural children (aged 9-12 in 2000) from Gansu, a poor province in China. In order to obtain consistent estimates of the effects of family background, we developed an instrumental variable approach to deal with the potential econometric problems caused by the unobserved child ability variables. Unobserved school quality is controlled by a set of school fixed effects. An error-ridden measure of child ability, the score of a cognitive ability test, is available to (imperfectly) proxy child ability. To

[23] Brown (2006) uses the same CDM as that in this paper. But he does not use the continuous measure of CDM, nor does he address the measurement error problem in it. Instead, he creates a dummy for children who scored higher than average.

deal with measurement error in this ability measure, a variables indicating the number of the parents who were born around the Great Famine in China, 1958-1961, are used as our instrumental variables.

This paper has two major findings, using the famine-IV approach. The first is the possibility that the strong household income effect found in the literature might merely reflect the effect of child ability. This paper shows clearly that income effect will be overestimated if child ability is omitted or if an ability measure is available but it contains a certain amount of measurement error.

The second finding is the significant effects of parental education, child characteristics and their interactions on math achievement. Father's education has significant impacts on both boys' and girls' academic skills, while mother's education is only significant for girls. Also, child gender matters greatly. The gender effect, together with the fact that more 500 mothers do not have any formal education, suggests that gender bias have long existed in formal education in rural China. Furthermore, the effects of father's education and mother's education differ across ability level. While father's education has a bigger impact for children with lower ability, mother's education has a bigger impact for more able children. These findings suggest the need for further research on household structure in rural China.

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Table 1. Variable Definition and Summary Statistics

Variable Name	Variable Definition	Mean	Std. Dev.	Min	Max
Dependent Variables					
Math Score	Score in math test	16.86	12.78	0	50
Family Background Characteristics					
Log(pcexp)	Log (expenditure per capita in *yuan*) [a]	6.80	0.71	4.34	9.62
Father education	Father's education measured in years of schooling	6.44	3.09	0	14
Mother education	Mother's education measured in years of schooling [b]	3.99	3.10	0	12
pcLand	Land holding per capita measured in *mu* per capita [c]	2.05	1.48	0	20
Child Characteristics					
Female	Dummy, =1 if a child is female	0.42	0.49	0	1
Age	Child's age measured in months	180.57	14.84	148	238
Age squared	Squared child's age measured in months				
Innate ability	Proxied by cognitive development measure (CDM) score	17.05	9.82	0	43

a. *Yuan* is the Chinese currency. One *dollar* = 8.27 *Yuan* in 2004.
b. 516 mothers have never been in schools.
c. *Mu* is the metric used in China to measure land size. One hectare = 15 *mu*.

Table 2. Results of Estimating Demand for Math Skills
Dependent variable = Math test score

Specifications	(1)	(2)	(3)	(4)
Ability	Omitted	Omitted	CDM as proxy	IV for CDM[b]
Estimator	OLS	2SLS[a]	2SLS	2SLS
Family Background				
Log(pcexp)	0.964	4.407	3.443	1.404
	(0.573)*	(2.121)**	(2.086)*	(2.683)
Father education	0.286	0.241	0.280	0.363
	(0.110)***	(0.114)**	(0.111)**	(0.136)***
Mother education	0.130	0.025	0.005	-0.036
	(0.118)	(0.135)	(0.131)	(0.146)
pcLand	0.438	0.329	0.315	0.288
	(0.310)	(0.320)	(0.311)	(0.340)
Child Characteristics				
Female	-0.821	-0.693	-0.511	-0.126
	(0.601)	(0.613)	(0.596)	(0.713)
Age	-0.901	-1.031	-1.057	-1.113
	(0.430)**	(0.443)**	(0.430)**	(0.471)**
Age squared	0.003	0.003	0.003	0.003
	(0.001)***	(0.001)***	(0.001)***	(0.001)**
Innate ability	---	---	0.335	1.044
			(0.043)***	(0.535)*
School fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.08			
No of observations	1643	1643	1643	1643

a. Log expenditure per capital is instrumented by Log value of durables per capita in year 2000.
b. CDM is instrumented by Famine-IV.
c.* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3. First-Stage Regressions of Specification (5) in Table 2.

Dependent variables	(1) CDM score in 2000	(2) Log expenditure per capita
Instruments		
Log (durable per capita in 2000)	0.543	0.169
	(0.224)**	(0.016)***
Number of Famine-born parents	2.319	-0.018
	(0.745)***	(0.053)
Family Background		
Father education	-0.087	0.007
	(0.070)	(0.005)
Mother education	0.118	0.022
	(0.075)	(0.005)***
pcLand	0.084	0.023
	(0.196)	(0.014)*
Child Characteristics		
Female	-0.548	-0.033
	(0.381)	(0.027)
Age	0.159	0.039
	(0.272)	(0.019)**
Age squared	-0.000	-0.000
	(0.001)	(0.000)**
School Fixed Effects	Yes	Yes
County Fixed Effects	No	No
R squared	0.08	0.11
Number of observations	1643	1643

a. Robust standard errors are in parentheses.
b. Household wealth is defined as value of durables.
c. *** Significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 4. Interaction Effects.

Specifications	(1) Family Background ×Gender	(2) Family Background ×Ability
Family Background		
Log(pcexp)	1.372	1.556
	(2.706)	(2.452)
Father education	0.373	1.836
	(0.137)***	(0.794)**
Mother education	-0.236	-4.283
	(0.178)	(0.852)***
pcLand	0.270	0.256
	(0.343)	(0.314)
Child Characteristics		
Female	-1.889	-5.720
	(1.111)*	(4.592)
Age	-1.130	-1.245
	(0.475)**	(0.435)***
Age squared	0.003	0.004
	(0.001)**	(0.001)***
Innate ability	1.082	0.547
	(0.541)**	(0.597)
Gender-Family interaction		
Female ×mother education	0.433	0.523
	(0.212)**	(0.201)***
Ability-Family interaction		
Ability ×father education	---	-0.085
		(0.045)*
Ability ×mother education	---	0.231
		(0.047)***
Gender-Ability interaction		
Female × Ability	---	0.194
		(0.272)
School Fixed Effects	Yes	Yes
Number of observations	1643	1643

a. Robust standard errors are in parentheses.
b. Household wealth is defined as value of durables.
c. *** Significant at 1% level; ** significant at 5% level; * significant at 10% level.