

## Chapter 2

# Data Collection and Methodology

**Abstract** This chapter first introduces the conceptual framework of the education production function, followed by a brief discussion regarding empirical issues in identifying the causal effects of various educational inputs on academic performance. Identification strategies including the control function, the instrumental variable model, and propensity score matching are then proposed. The data collection process, which was based on careful and thorough research procedures, is reported in detail.

### 2.1 Conceptual Framework Guiding the Empirical Studies in This Book

The empirical approaches used in this book were tailored to an analysis of various treatment effects on NCEE performance. The general conceptual framework involves the classical education production function, and the design of appropriate educational inputs.

The education production function is a mathematical relation that describes a series of maximum educational outputs that can be produced with given educational inputs and technology (Cohn and Geske 1990, p. 168). A generalized version of the education production function can be expressed as follows:

$$f(Q, X|S) = 0$$

where

$Q$  is the vector of educational outputs:  $Q: q_1, q_2, \dots, q_n$

$X$  is the vector of family inputs:  $X: x_1, x_2, \dots, x_k$

$S$  is the vector of school related inputs:  $S: s_1, s_2, \dots, s_m$ .

Thus, there are  $n$  outputs and  $k + m$  inputs, and  $f$  is the functional operator.

Although the functional form is uncertain, a linear relationship between the inputs and the outputs is empirically valid within a certain, small range of data in which the linear approximation is reasonable (Cohn and Geske 1990). It should be

noted that any conclusion derived from linear analysis cannot be applied to input levels beyond the range of the data sample.

For a linear model, the general form of the  $i$ th production function is:

$$q_i = a_i + \sum_{g=1}^n b_{ig} q_g + \sum_{h=1}^k c_{ih} x_h + \sum_{j=1}^m d_{ij} s_j + e_i$$

where  $a_i$  is the intercept, and  $b_{ig}$  and  $c_{ih}$  are the coefficients to be estimated. The coefficient in a linear function is defined as a constant marginal productivity of the corresponding input, and  $e_i$  is a stochastic error term.

Educational inputs possess a hierarchical structure with at least five levels: the society level, community level, school level, classroom level, and student level. The society and community levels constitute the external context of the school (Bourdieu 1986; Coleman 1988), and are not the focus of this study. School-level inputs can be classified as institutional or physical inputs. Institutional inputs include principal leadership, school culture, school-level student composition with regard to socioeconomic status (SES), student study abilities, and other factors. Physical inputs refer to school-level resources such as per student expenditure, equipment, libraries, facilities, and building characteristics. Classroom-level inputs include teacher effects such as teacher experience, teacher expectations, and peer effects from the perspectives of gender, study ability, and SES. Student-level inputs can be divided into student inputs and family inputs, as well. Student inputs include gender, academic track, and study ability; family inputs include family SES, parenting styles, household educational spending, and private tutoring.

A key objective of the econometric estimation of the educational production function is identifying causal relationships of interest, i.e., the achievement effect of a certain type of educational input. All quantitative approaches must be informed by the causal theory, i.e. the general form of the education production function. However, due to the complexity and selectivity inherent to the education production process (as discussed later in this chapter,) and the difficulty in identifying and quantifying inputs (Cohn and Geske 1990), the classical assumptions of ordinary least square (OLS) regression may be violated, and/or the estimated coefficients might be biased. In effort to remedy this, more sophisticated models (including both experimental and non-experimental designs) are proposed here to identify causal relationships of interest.

According to Angrist and Pischke (2009) and Blundell and Dias (2009), there are several available approaches to identifying causal effects: randomly controlled trial (RCT), natural experiment methods (i.e. differences-in-differences methods, [DID]), discontinuity regression (RD) methods, propensity score matching (PSM), instrumental variable (IV) methods, control function (CF) methods, and quantile regression (QR). RCT is the gold standard of causal inference; RD and matching approaches attempt to mimic the randomized assignment of an experimental setting with non-experimental data. The successful adaption of these identification

strategies is dependent on whether the model hypotheses are valid for the specific data structure being utilized.

Based on the conceptual framework and general knowledge of causal inference models, this study proposes appropriate empirical models to fit different situations and attempts to successfully identify the causal effects of various educational inputs.

## 2.2 Methodological Issues in NCEE Analyses

In general, the most dangerous problem one must avoid during this type of analysis is the omitted variable bias (OVB). If the key variable of interest is a categorical variable, this bias is also called “self-selection bias.” Students self-select different treatment groups or control groups according to their own characteristics (which also affect NCEE performance,) so the estimated treatment effects are biased if some of these characteristics are not controlled during regression.

Various causal inference models can be utilized to address the OVB problem. This book generally employs three such approaches, which are discussed throughout this section; they include the control function model (CF), propensity score matching (PSM), and the instrumental variable model (IV).

### 2.2.1 Basic Model and Omitted Variable Bias

The basic model of the education production function enables a detailed discussion of techniques. See the following equation:

$$NCEE_{ik}^* = \alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + u_{ik} \quad (2.1)$$

where  $NCEE_{ik}^*$  is the NCEE score of student  $i$  in school  $k$ ,  $X_{ik}$  is a vector of student characteristics (gender, academic track, *hukou*, study ability, SES, family financial background, and parenting styles,)  $S_k$  is a vector of school-level inputs (average teacher quality, physical school inputs, and school administrative styles,) and  $u_{ik}$  is the error term. Table 2.1 details all instruments used to construct the models. Most variables were designed according to previously published studies, and some were designed according to pilot studies.

In China, lower secondary graduates are not randomly assigned to high schools, but instead compete for enrollment in elite schools, primarily through the HSEE and other unmeasurable factors such as social networking. However, because the unmeasurable factors are left in the residual term, this factor may be correlated with school-level educational inputs  $S_k$ , which represent the high school selection result. Therefore, the classical assumption of ordinary least square (OLS) regression is violated, and the coefficient of  $S_k$ , (i.e.,  $\alpha_2$ ), is biased; OVB is a result, then, because the omitted variables caused bias.

**Table 2.1** Instruments used for modeling

Category	Instruments	Measurement or comments
Student level characteristics	Gender	Dummy variable: female = 1, male = 0
	Academic track	Dummy variable: science track = 1, humanities track = 0
	Registered residence	Dummy variable: rural = 1, urban = 0
	Student ability	HSEE score as pre-existing difference in academic ability
	Socioeconomic status	SES index calculated from individual variables including parental education level, parents' professions
	Parenting style	Four indices calculated from a series of instruments measuring parents' style of involvement in child's education
	Teacher quality	Teacher credential variables (categorical variables) and teacher assessment score (continuous variable)
School level inputs	School selectivity	HSEE admission line
	School size	Number of students
	Average teacher quality	(1) Percentage of teachers with certain professional ranks
		(2) Percentage of teachers at certain education levels
	Physical school inputs	(1) Student-to-teacher ratio index
		(2) Index calculated from the scale and condition of laboratories
		(3) Computer index calculated from computers per student in total, and computer per student used during instruction
	School climate and administration	(1) Principal leadership type measured by aggregated categorical evaluation scores from teachers in terms of teacher development, high authority and accountability, and lax leadership
		(2) School's effort spent on extra curriculum and cultural activities measured by aggregated evaluation from students

### 2.2.2 Control Function Model

There are at least two ways to address the school-level self-selection bias: CF and PSM. In this section, CF is employed to define and address the self-selection bias generated during high school assignment.

Based on an original idea proposed by Heckman (1979), the three currently prevailing approaches were suggested by Lee (1983), Dubin and McFadden (1984),

and Dahl (2002). According to theoretical analysis and Monte Carlo analysis, it has been concluded that in most cases, the approaches proposed by Dubin and McFadden (1984) and Dahl (2002) are preferable over the Lee method. The Dubin and McFadden (1984) correction method waives the restriction under which all correlation coefficients must sum-up to zero (Schmertmann 1994; Bourguignon et al. 2007). This study adopts the Dubin-McFadden approach.

Suppose that individual student  $i$ 's utility function in selecting school  $k$  is:

$$I_{ki}^* = W_i \delta_k + \eta_{ik} \quad (2.2)$$

where  $W_i$  is the exogenous and pre-treatment variable that determines school selection  $HSEE_{ik}$ ,  $\delta_k$  is the vector of coefficients, and  $\eta_{ik}$  is the error term, which is independent and identically Gumbel-distributed (i.e., the IIA Hypothesis, or independence of irrelevant alternatives.).

Individual student  $i$  will select school  $k$  if and only if school  $k$  maximizes utility function (2.2). Define  $I_i$  as individual  $i$ 's school selection indicator.

$$\begin{aligned} I_i &= k \quad \text{iff } I_{ki}^* > \text{Max}_{ni}^* \quad (k \neq n) \\ &= 0 \quad \text{otherwise.} \end{aligned}$$

For this truncated data, one only observes the NCEE score for student  $i$  who selects school  $k$ :

$$\begin{aligned} NCEE_{ik} &= NCEE_{ik}^* \quad \text{iff } I_i = k \\ &= ? \quad \text{otherwise} \end{aligned}$$

Let  $\varepsilon_{ki} = \text{Max}_{nk}^* - \eta_{ik}$ , thus  $I_i = k \quad \text{iff } \varepsilon_{ki} < W_i \delta_k$ .

Assume that  $\varepsilon_{ki}$  has an extreme value distribution, and is independent and identically distributed (IID).

$$\begin{aligned} F(\varepsilon_{ki}) &= \exp(-\exp(-\varepsilon_{ki})) \\ f(\varepsilon_{ki}) &= \exp(-\varepsilon_{ki}) \exp(-\exp(-\varepsilon_{ki})). \end{aligned}$$

The conditional multinomial logit model is:

$$\Pr(\varepsilon_{ki} < W_i \delta_k) \equiv \Pr(I_i = k) = \frac{\exp(W_i \delta_k)}{\sum_{k=1}^K \exp(W_i \delta_k)}, \quad k = 1, 2, \dots, K \quad (2.3)$$

$$\begin{aligned}
& E[NCEE_{ik}^* | X_{ik}, S_k, I_i = k] \\
&= E[\alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + u_{ik} | X_{ik}, S_k, I_i = k] \\
&= \alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + E[u_{ik} | X_{ik}, S_k, I_i = k] \\
&= \alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + E[I_i = k] \\
&= \alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + E[\varepsilon_{ki} < W_i \delta_k] \\
&= \alpha_0 + \alpha_1 X_{ik} + \alpha_2 S_k + \sigma \frac{\sqrt{\sigma}}{\pi} \left[ \sum_{s \neq k} r_{ks} \left( \frac{P_s \ln(P_s)}{1 - P_s} \right) - r_{kk} \ln(P_k) \right] + v_{ik} \quad (2.4)
\end{aligned}$$

where  $r_{ks}$  is a correlation coefficient between  $u_{ik}$  and  $\eta_s$ .

At this point, Eq. (2.4) generates unbiased estimation of  $\alpha_2$ . In fact, the results are unbiased even when the independence of irrelevant alternatives (IIA) assumption is violated (Bourguignon et al. 2007).

It is important to mention that the CF model based on a multinomial logit model will derive  $k$  regressions for the outcome equation due to the inherent nature of the multinomial logit model. If the schools are collapsed into three categories, three sets of estimates must be presented for each category.

### 2.2.3 Propensity Score Matching

Propensity score matching can be used to describe average treatment effect (ATE) as a whole, rather than estimating the effect of each factor in the treatment (which is essentially what a CF model does). Detailed definitions for some of the terms used here (treatment, variables in  $X$ , and additional analysis,) will be provided later, when PSM is applied.

The general idea of PSM is constructing a comparable control group for the treated group, and then comparing the mean difference of the outcomes as if the two groups had been randomly assigned. The first step of this approach is to model the selection process and estimate the propensity score of each student having received treatment. The PSM logit model is as follows:

$$\Pr(T_i | \bar{X}_i) = \pi_0 + \bar{\pi}_1 \bar{X}_i + \eta_i \quad (2.5)$$

where  $T_i$  is the treatment assignment variable, and the vector  $X_i$  represents the variables that determine the selection of treatment.

In the second step of PSM, the nearest-neighbor method is employed for matching.

### 2.2.4 *Instrumental Variable Model*

The instrumental variable (IV) approach is specifically designed for private tutoring participation, which is considered an endogenous variable. The most crucial and important part of IV design is to identify valid IV, which can be rather difficult. (Because IV is only applied to the private tutoring variable, it is not discussed here in detail—a brief model setup is presented in Sect. 4.4.)

## 2.3 Data and Sampling Strategy

### 2.3.1 *Background of Jinan City*

Based on the empirical models discussed above, the data required to conduct this study was hierarchical data nested at the student level, classroom level, and school level. Individual student-level data included student background information, test scores, parents' pecuniary and non-pecuniary inputs in education, and detailed information on private tutoring participation. Classroom-level data included overall classmate characteristics, teacher quality, and class atmosphere. School-level data included inputs such as teacher quality, labs and libraries, organizational administration style, and school-level peer effects.

The Chinese database required was not available to the author. There were several potential causes of this data constraint: first, there may have been appropriate databases to facilitate this study that are restricted to government use and not open to the public; second, of the databases used by existing studies in China, most are characterized by low quality and limited information in addition to being unavailable for use by other authors; and third, a high-quality, second-hand dataset with all needed information is difficult to establish due to the expertise and large amount of resources required for such a database. Thus, data collection proved the only way to successfully conduct this study.

The author collected data in Jinan City, the capital of Shandong Province in eastern China. Jinan was ultimately selected for several reasons. First, Shandong Province has one of the largest student bodies in China, making it an excellent representative of Chinese education policies. In 2010, about 660,000 students<sup>1</sup> took the NCEE in Shandong—the second-largest population of NCEE testers across all provinces. Second, Jinan is a typical city in Shandong, with a significant amount of socioeconomic variation across its ten districts. The province had 41 regular senior high schools of varying quality as of 2009.<sup>2</sup> Third, Jinan is above the average

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<sup>1</sup>Data source: iqilu.com.

<sup>2</sup>Data source: *Jinan Education Statistic Yearbook 2009*.

province level in terms of both population and economic development; the Gross Domestic Product (GDP) of Jinan in 2007 was 256.281 billion RMB, which accounted for 9.9 % of the total in Shandong Province.<sup>3</sup> The per capita GDP of Jinan was 43,952 RMB in 2007, ranking fifth in Shandong overall.<sup>4</sup> Thus, there was expected to be a considerable amount of private tutoring data available for Jinan City without sacrificing representativeness.

Shandong had a population of 93,669,700 in 2007.<sup>5</sup> The GDP of Shandong province was 2588.770 billion RMB (about 370 billion USD) in 2007; the province ranked second across all 31 provinces in China, just behind Guangdong Province.<sup>6</sup> The per capita GDP in Shandong was only 28,000 RMB, however, falling to seventh place among all provinces in China.<sup>7</sup> Jinan lies in the middle west of Shandong, with a population of 6,048,500 in 2007, out of which urban<sup>8</sup> population comprised 58.3 %. The urban registered unemployment in Jinan was 5.43 % in 2007. There are 10 county-level districts in Jinan: Lixia District, Central City District, Huaiyin District, Tianqiao District, Licheng District, Changqing District, Zhangqiu City, Pingyin County, Jiyang County, and Shanghe County. The latter four are counties just outside the urban area of Jinan. The basic socioeconomic indicators of the area are listed in Table 3.3 (Tables 2.2 and 2.3).

Data was collected through questionnaire survey and administrative data collection methods. Administrative data included HSEE scores, NCEE scores, school revenue and expenditure, student tuition and school choice fees charged by each school, county-level socioeconomic indicators, and other relevant factors. Administrative data is typically more precise and avoids self-selection bias. Questionnaire data is discussed in detail in a later section.

### 2.3.2 Sampling Strategy

In 2007, 60,302 Grade 9 students took the HSEE in Jinan. Among them, 40,500 students were then enrolled in 43 regular high schools (RHSs), including 37 public high schools and six private high schools.<sup>9</sup>

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<sup>3</sup>Data source: *Jinan Statistic Yearbook 2008*.

<sup>4</sup>Data source: <http://zhidao.baidu.com/question/61711995.html>.

<sup>5</sup>Data source: *Jinan Statistic Yearbook 2008*.

<sup>6</sup>Data source: Shijie 2007 Nianjian (*World Yearbook 2007*), China Finance and Economic Publishing House.

<sup>7</sup>See footnote 6

<sup>8</sup>“Urban” indicates urban registered residence.

<sup>9</sup>Data source: *Jinan Education Statistics Yearbook 2007 (2007 ji nan shi jiao yu tong ji shou ce)*.



**Table 2.2** Socioeconomic indicators in Jinan, 2007

District	Population (unit thousand)	Per capita GDP	Regular budgetary expenditure (unit million RMB)	
		unit RMB	All sectors	Education sector
Whole City	6048.5	42371.00	9880.38	2170.78
Lixia District	575.3	75722.23	966.41	194.35
Shizhong District	568.5	57120.49	903.75	222.17
Huaiyin District	373.5	35295.85	696.78	142.37
Tianqiao District	504	43351.19	793.78	169.48
Licheng District	935	55182.89	1697.12	395.17
Changqing District	570.8	28740.36	758.66	197.52
Pingyin County	368.7	29582.32	586.19	126.74
Jiyang County	609.7	19696.57	695	140.82
Shanghe County	539.2	10736.28	547.88	143.69
Zhangqiu City	1003.8	32060.17	2234.81	438.47

Data source: *Jinan Statistical Yearbook 2008*

**Table 2.3** Target cohort and senior high school promotion rate (unit student)

	Urban school	County school	Rural school	Total
Lower secondary graduates in AY 2006–07	22593	17812	19676	60081
Upper secondary freshman in AY 2007–08	20328	13968	0	34296
Senior high school promotion rate (5)	89.97	37.26		57.08 %

Data source: Jinan Shi Jiaoyu Tongji Shouye (*Jinan Education Statistic Yearbook 2007–2008*)  
AY academic year

Taking into account the feasibility of data collection and the significant difference between public and private schools,<sup>10</sup> this study only focuses on public, RHS students. A stratified, non-proportional sampling strategy was employed according to the school system characteristics. The study sample was derived from 25 schools out of the 34 public RHSs across all nine districts and counties<sup>11</sup> in Jinan; total schools sampled account for 71 % of all public RHSs in Jinan. Among the 25 selected schools, 15 are urban, eight are counties, and two are rural schools. The proportions of sampled schools in urban, county, and rural areas account for 71, 73,

<sup>10</sup>High-quality schools are all public schools. As discussed above, private schools basically attract students from wealthy families and with lower academic achievement.

<sup>11</sup>One district (Huaiyin) out of ten does not have a senior high school.

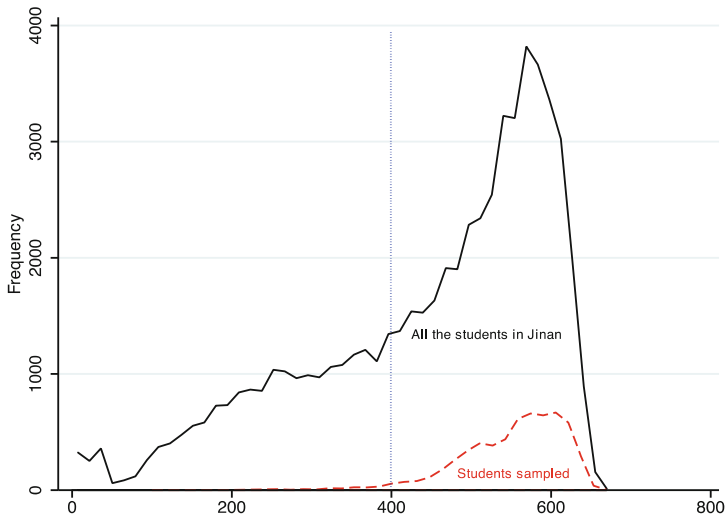
**Table 2.4** School sampling by location

	Urban	County	Rural	Total
All public regular high schools in Jinan	21	11	3	35
Selected public regular high schools	15	8	2	25
Percentage (%)	71	73	67	71

and 67 % of all public RHSs in the three areas, respectively. Overall, the 25 sampled schools are representative of all the public RHSs in Jinan (Table 2.4).

Within each high school, three to five classes were randomly chosen (though guaranteed to cover all kinds of class types, including science and humanities tracks within the academic track dimension, and key, non-key, and panel classes within the study ability grouping dimension). All students in the selected classes (about 50 to 60 students per class) were sampled. For a population of 40,000 students (not excluding students enrolled in private schools,) the margin of error for a sample with 6000 students was 1.17 %.

Figure 2.1 compares the frequency of the total HSEE scores of all junior middle school graduates in Jinan in 2007 with that of the students sampled. The lowest official admission line was 400, but there were some high school students admitted with scores below 400. The distributions of the population and the sample are quite similar. A *t*-test for students with HSEE total scores higher than 400 showed that the mean score of students sampled is 15 points higher than the mean of all students



**Fig. 2.1** Frequency of the HSEE total score in 2007: All junior middle school graduates in Jinan versus students sampled

in Jinan. Fifteen points only accounts for about for 2 % of the full mark (690 points,) thus, the sample selection bias is very modest.

2.4 Data Collection and Fieldwork

Data was collected with the help of the Jinan Education Bureau (JEB), who issued an approval letter for the survey and informed all the principals in the public schools in Jinan about this study. An information reception was held by JEB for the principals of participating schools, during which the vice director of the JEB introduced this research project, explained its significance to the Jinan education system, and asked the principals to assist in distributing the survey. The survey schedule (formatted as shown in Table 2.5) was framed under an agreement with all the principals of participating schools. Principals were able to be contacted by the author by cell phone if necessary for clarification during data collection.

In late February 2010, just after the start of the spring semester, the research team recruited from Shandong Normal University went to different high schools with the approval letter from the JEB and, following the survey schedule, distributed the questionnaires and collected them once they were complete. All the student questionnaires, teacher questionnaires, and principal questionnaires were retrieved by the research team on the same day of the school visit. Parent questionnaires were collected one week later, because most schools were boarding schools, so students needed weekends to bring the parent questionnaires home then back to school to turn them in. All the collected questionnaires were distributed and returned in sealed envelopes. The entire on-site survey took ten days.

The questionnaires as-received were then delivered to a questionnaire company (QC) for data processing. There were several advantages to employing a QC instead of student volunteers for data entry and processing. The selected QC, for one, is a professional academic questionnaire company with a business license issued by the government and a favorable reputation in privacy protection among the major education research institutes in Beijing, better ensuring the accuracy and legitimacy

Table 2.5 Survey schedule format

Item	Content surveyed for each school
School	Name
Contact person	Name
Phone	Number
Address	Address
Research assistant	Name
Phone	Number
Questionnaire distribution date	MM/DD, a.m. or p.m.
Parent questionnaire collection date 1	Next day after distribution date, a.m./p.m.
Parent questionnaire collection date 2	Next monday after distribution date, a.m./p.m.

of this study's results. Data confidentiality was effectively protected by signing an agreement with the QC. In addition, the total number of questionnaires was around 12,000—the work load to perform this much data entry was must better suited to a professional company than to student volunteers.

Data processing quality was guaranteed by both the dual-independent data entry procedure and random inspection by the author. The error rates were 0.45 % for independent data entry 1, and 0.24 % for independent data entry 2; thus, the possibility of any mistake in data entry is 0.001 % ( $0.45 \% * 0.24 \%$ ).

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