Education, Worker Productivity, and Income Distribution in China

Team

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1. Introduction

We propose that a basic cause of high and rising regional income inequality in China is attributable to underinvestment and to misallocation of investment in higher education that is both an effect and a cause of low incomes in the relatively disadvantaged areas and provinces of China. In the early years of its economic reform in the late 1970s through the end of the 1980s, regional inequality as measured by the coefficient of variation of provincial per-capita income fell from nearly unity to approximately 0.6. Since then, the trend has reversed so that by the year 2001, this measure of regional inequality stood at 0.76 (Chen and Fleisher, 1996, Chang, 2002). This rising inequality in part reflects the relaxation of income equalizing policies that characterized regulated wage grids under central planning (Fleisher, Sabirianova, and Wang, 2004), but that is clearly not the entire story. According to Yang (1999), China in the late 1990a surpassed almost all countries in the world for which data are available in rising income inequality, and by the year 2000 China found itself with one of the highest degrees of income inequality in the world (Yang, 2002).

Rising income inequality has been assigned a number of causes including urban bias, regional favoritism, and corruption in the reform process. Fleisher and Chen (1997) found that China's high and rising regional income inequality reflected a wide, and perhaps growing, dispersion of labor and total-factor productivity which, in turn, they attribute to regional inequality of investment in higher education. Evidence of underinvestment in human capital, particularly at the higher-education end has been corroborated in research by Fleisher and Wang (2001, 2003 and 2004). Heckman (2004) shows that expenditure on higher education in China remains characterized by extreme regional inequality and that there is a serious imbalance between investment in physical and human capital. In the past decade, total expenditure on higher education in China has grown rapidly and the contribution of private expenditures has outpaced the growth of government expenditures (Zhang, Zhao, Park, and Song, 2005). A critical question, though is whether this change in mix of support for higher education has encouraged those with the most to gain to attain higher educational attainment. If not, then the educational resources may be allocated inefficiently, and income inequality may be exacerbated if the poorest segment of the population who may benefit significantly from more schooling is excluded.

Given the extent of educational achievement, another important question is whether pay gains match productivity gains attributable to more schooling.. We will estimate the effect of education on marginal productivity of labor and investigate the extent to which incomplete labor markets have so far failed to fully reward higher levels of schooling, which discourages private investment in education. Moreover, to the extent that higher education is subsidized with public funds, these expenditures are biased in favor of high-income regions, so that in the presence of imperfect and incomplete credit markets for investment in human capital, regional income and productivity gaps are exacerbated. We will measure the social return to education in production, both direct and through spillover effects on other firms or enterprises. These estimates will yield very useful results in at least three areas. First, by comparing private and social returns to education, we gain important insight on the development of China's labor market. Secondly, the estimated returns will provide a base from which to study the private demand for education and how it is affected by perceived returns to schooling and by uncertainty and borrowing constraints. The results will provide a sound basis for policy recommendations for government policies on education, including the regional distribution of funds. The information will help to evaluate educational policies that can be used to reduce regional income disparity in China through investment in human capital.

A distinguishing feature of our proposal is that we study the effects of education from two aspects: (1) the effect of education on individual earnings; (2) the effect of education on productivity. In perfectly functioning market economics, these two effects are closely related, although not necessarily equal. However, in China's transition economy they are likely to diverge significantly (Fleisher and Chen, 1997, Fleisher and Wang, 2001, Fleisher and Wang, 2003) in large part due to barriers and restrictions in China's labor markets and the degree of competition among firms. The deliverable output will highlight how the returns to schooling in terms of income reflects the efficiency of the current educational funding system and the degree to which it approaches the return in production. We will estimate the treatment effect of adding more college-trained workers to the labor force across regions with an emphasis on identification of any misallocation of educational and labor resources. We will provide these estimates for urban areas according to geographical, economic, and political characteristics. The impact of current policy on productivity and income distribution will be addressed. Policy recommendations for improving the allocation of educational expenditures, the efficiency of labor markets, and their impact on income inequality will be provided.

2. Background

We do not have a single 'best' estimate of the impact of higher education on income and production in China, but evidence from both aggregate and disaggregate data, across regions, across rural and urban sectors, and across various ownership types consistently supports the hypothesis that its impact on production is significant and substantial. What are the likely sources of this relationship? They are to be found in the myriad ways that highly-skilled and talented individuals increase productivity both directly and indirectly through the allocation of resources and adopting and adapting new technology as cited widely in the growth literature. Although China under Communist planning largely eliminated illiteracy and achieved a high level of primary-school graduation, public support of investment in higher education lagged seriously during and after the Cultural Revolution, and China trailed other countries at comparable stages of development (Table 1 and Table 2).

There is recent evidence that the relative scarcity of college graduates has begun to pay off in terms of earnings; these higher relative earnings may now be providing greater incentives for people to obtain higher education. However offsetting the increasing incentive effects of a growing premium for educated workers, families at lower end of the income distribution face the double constraint of inadequate credit and rising schooling fees, which exacerbates China's widening income gap. In the past decade, China has vastly expanded expenditures on education overall but still lags its counterparts in terms of proportion of GDP spent (Table 3 and Table 4).

Moreover, a critical aspect of China's policies toward higher education has been inappropriate. Educational expenditures have been disproportionately directed toward areas where the rate of return is relatively low, and this has important policy implications for efforts to promote economic growth and to reduce regional income inequality through encouragement of investment in physical capital (Table 5). These expenditures partially cause and additionally reinforce a gross inequality of the regional allocation of educated persons (Tables 6-8). Moreover, they reinforce regional differences in labor productivity that are exacerbated by restrictions on labor migration and the difficulties that migrants face in obtaining public support for education. Although national and local laws require that the municipality of residence (whether or not one's *hukou* grants permanent residence rights) is responsible for providing nine years of primary schooling for each child., in practice this right is often denied. The result is that migrant families must pay fees ranging from 3,000 to 30,000 *yuan* per year per child to have their children admitted to the regular school system or cooperate with other migrant families in providing their own schools and teachers. Even so, newspapers often contain reports of migrant schools being torn down by public authorities on grounds that they provide inferior schooling or are safety hazards (which are probably true claims; see e.g., Xie, 1999). Obviously, their access to schooling at the secondary level and beyond is subject to even greater restrictions.

3. Research Plan

3.1 Methodology

We will conduct a comprehensive investigation of the effects of education in China on production and on personal income, using both firm level survey data and household survey data, using the most advanced methods available.

First, we will estimate private (individual) returns to education based on individual earnings. We will identify the average treatment effect of education by allowing for heterogeneous returns among individuals selecting into schooling based on their personal characteristics and perceived returns. This will be done using a semi-parametric framework that accounts for heterogeneity, selection, and for funding constraints following Heckman and Li (2004) and Carneiro, Hansen, and Heckman (2003). These estimates will be compared with conventional approaches (ordinary least squares estimation or instrumental variable estimation) which do not account for heterogeneity in returns on which individuals select into schooling. We will utilize information regarding regional and over-time variation in public expenditure on education to identify the effects of funding constraints on schooling choices. We will show the extent to which changes in educational funding and increased reliance on private financing of higher education have increased or reduced the efficiency of the allocation of educational resources in China.

3.1.1 Individual Returns to Schooling. Our method takes into account both heterogeneous returns to schooling and self-selection based on anticipated returns. We first estimate the marginal treatment effect (MTE) in the sample, which is the building block of other parameters of interest. The marginal treatment effect and its derivatives are estimated using the method developed in Heckman, Ichimura, Todd, and Smith (1998).[i, ii]

We set up the following model of wage determination by schooling choice:

$$\ln Y_1 = \mu_1 \left(X, U_1 \right)$$
$$\ln Y_0 = \mu_0 \left(X, U_0 \right)$$

where a subscript indicates whether the individual is in the schooled state (1) or the unschooled state (0). Y is income, X is observed heterogeneity, and U is unobserved heterogeneity in wage determination. In general, the functional forms can have a nonlinear component, and $U_1 \neq U_0$.

The schooling choice comes from the following latent dependent model:

$$S^* = \mu_s(Z) - U_s$$
$$S = 1 \ \ if \ \ S^* \geq 0$$

where S^* is a latent variable whose value is determined by an observable component $\mu_s(Z)$ and a unobservable component U_s. A respondent will only attend college (i.e. S=1) if this latent variable turns out to be nonnegative.

In our empirical work, Z is a vector of variables that help predict the probability of attending college. It includes parental education, parental income, number of children (siblings), gender, ethnic group, and birth year dummies. On the other hand, X is a vector that holds explanatory power on wages. In the benchmark setting, this includes work experience, work experience squared, gender, ethnic group, ownership, industry, and location. Z and X can share some common variables, but Z must also possess unique variables for the model to be identified.

In the first step, a probit model is used to estimate the $\mu_s(Z)$ function. The predicted value is called propensity score, $\hat{P}_i$, where the subscript *i* denotes each individual. The second step adopts a semi-parametric procedure in which *local linear regressions* are used. Fan (1992, 1993)[iii] develops the distribution theory for the local linear estimator of $E(Y|P=P_0)$, where Y and P are random variables. They show that $E(Y|P=P_0)$ and its derivatives can be consistently estimated by the following algorithm:

$$\min_{\gamma_1,\gamma_2} \sum_{i \leq N} \left[Y_i - \gamma_1 - \gamma_2 \left(P_i - P_0\right)\right]^2 G\left(\frac{P_0 - P_i}{a_N}\right)$$

where γ_1 is a consistent estimator of $E(Y|P=P_0)$, and γ_2 is a consistent estimator of $\partial E\left(Y \mid P = P_0\right) / \partial P$. G(.) is a kernel function and a_N is the bandwidth. We use a Gaussian kernel and a bandwidth of 0.2 in the estimation.[iv] Obviously, this algorithm is equivalent to applying weighted least square at each observation point, only using samples in its nearest "neighborhood".

We first estimate E(lnY|P) and E(X|P) with the above procedure. Then we run the *double residual regression* of lnY-E(lnY|P) on X-E(X|P). This is a simple OLS regression, except we trimmed off the smallest 2% of the estimated propensity scores with a biweight kernel as suggested by Heckman, Ichimura, Todd, and Smith (1998). The result is consistently estimated coefficients of the linear components of the model, β.

Define the nonlinear component residual as U=lnY- βX. Use local linear regression again to estimate E(U|P) and its first derivative. This first derivative is the marginal treatment effect (MTE). The average treatment effect (ATE) is a simple integration of the MTE with equal weight assigned to each $P(Z)=U_s$. However, treatment on the treated (TT) and treatment on the untreated (TUT) are calculated with the following weighting functions:

$$h_{TT}(u_s) = \frac{\left[\int_{u_s}^{1} f(p)\,dp\right]}{E(p)}$$

$$h_{TUT}(u_s) = \frac{\left[\int_{0}^{u_s} f(p)\,dp\right]}{E(1-p)}$$

where f(p) is the conditional density of propensity scores. The conditioning on X is implicit in the above functions. All integrations are conducted numerically using simple trapezoidal rules.

3.1.2 <u>Returns to Schooling in Production. W</u>e will measure the return to education (social return) by its contribution to production. Such a contribution includes a direct contribution to marginal productivity of workers and an indirect contribution to a firm's total factor productivity and efficiency. The social return will be compared to the private return as reflected in workers' wages. We will specify a general production function as follows:

$$Y_{it} = f(L_{sit}, L_{pit}, X_{it}) + u_{it} \qquad (1)$$

where Y is output, L_p is the number of production workers, L_s is the number of skilled/technical workers, X represents other inputs, and u is a disturbance term, for firms i= 1, 2, …, n from year t=1, 2, …, T. Potential choices of production function specification include Cobb-Douglas (CD), translog (TL), and constant elasticity of substitution (CES). Empirical tests will be conducted to select a suitable functional form.

In this study, we will investigate both direct and indirect effects of human capital in China, the direct affect being through the marginal productivity of an individual worker and the indirect effect being through total factor productivity. Mankiw et al. (1992) advocate the direct approach, while Islam (1995) and Benhabib and Spiegel (1994) find that human capital does not contribute significantly to explaining output directly; they suggest that human capital mainly affects total factor productivity.

We will proceed in the following steps.

A. Test Firm's Objective

The ownership structure of Chinese firms may lead to multiple objectives, especially for state- and collectively-owned enterprises. A reasonable set of goals includes profit maximization, generating employment, and increasing wages (in the spirit of the labor-managed firm). A firm's objective will influence employment decisions and the observed relationship between value of marginal product and wage. Following Svejnar (1986), the firm's objective is specified as a geometric average of the above three goals:

$$U = L^{\alpha l}(W - Wa)^{\alpha w}\Pi^{(1-\alpha l-\alpha w)} \qquad (2)$$

where L is total labor, W is wage, W_a is alternative wage, and Π is profit. We will follow Brown and Ashenfelter (1986) and Svejnar (1986) in specifying an empirical model obtained by maximizing equation (2) subject to a CES production function. Estimates based on this model will provide an indication of firm objectives. The estimation will be performed for each ownership sector.

A. Estimation of the Production Function

The production function (1) will be first estimated assuming technical efficiency via ordinary least squares (OLS) and fixed effects (FE) techniques.. Additionally, given the possibility of input endogeneity, we apply instrumental variable (IV) estimation in combination with the FE approach.

Possible instruments include:

a. basic wages, treated as administratively set by the government. Elements of the wage "grid" will be estimated from household survey data.
b. supply-side variables in the labor market, which should be uncorrelated with demand-side variables influencing a firm's production decisions. In the current firm level data, we have two such variables that can be used as instruments:
    - i) the number of applicants for each category of jobs (worker category) as reported by the firms in the survey.
    - ii) the time taken to fill the last job in each category of worker.
c. local inflation measures
d. local unemployment rate or number of laid off workers.

C. Worker Marginal Products and the Direct Effect of Education

The direct effect of education on production is measured by its impact on worker marginal product, which is easily derived from the estimated output elasticity for each type of worker from either conventional estimation of the production function or from the stochastic production frontier.

For example, in the case of Cobb-Douglas technology, the marginal product of production workers and skilled workers for firm i at year t can be expressed as

$$MP_{pit} = \frac{\partial Y_{it}}{\partial L_{pit}} = \beta_{pj} \cdot \frac{Y_{it}}{L_{pit}}$$

and $$MP_{sit} = \frac{\partial Y_{it}}{\partial L_{sit}} = \beta_{sj} \cdot \frac{Y_{it}}{L_{sit}} \qquad (6)$$

If the average education level for production workers is E_p and for skilled/technical workers is E_s then, the annual rate of return to education for each firm (ignoring direct schooling costs) ρ_{it} can be calculated as

$$\rho_{it} = \left(\frac{MP_{sit}}{MP_{pit}}\right)^{\frac{1}{E_s - E_p}} - 1 . \qquad (7)$$

Clearly, the rate of return is a function both of output level , the quantities of technical/skilled workers, and their respective output elasticities. We can use sample averages to calculate the average annual rates of return based on equation (7), and we can allow for the possibility of intercity or inter ownership-sectoral differences in output elasticities. By comparing the value of marginal product of each type of worker with their respective average wages we can draw inferences regarding a firm's objectives and the influence of labor market institutional constraints (e.g. monopsony power). We will combine the results from firm data and individual data to discuss the difference in estimated effects of education on production and on earnings and their implications for China's education, labor-market, and income-distribution policies, and the implications for human capital investment in China and for policies addressing sectoral, regional, and individual income inequality.

In order to identify the effect of education on production, we assume that less educated workers can be converted to highly educated workers by sending them to school for a sufficient number of years. Define *sw* to be the number of *additional* years of schooling required (the difference in average years of schooling between highly educated and less educated workers) to convert one worker with low education into a worker with high education. Under the simplifying assumptions (also basic to the standard Mincer equation) that the only opportunity cost of investing in a highly educated worker is the foregone marginal product of the less-educated worker and that the production gain is a constant, infinite stream, then

$$MPs_i = (1 + r_i)^{sw_i} MPp_i \,, \tag{1}$$

or

$$\frac{MPs_i}{MPp_i} = (1 + r_i)^{sw_i} \tag{2}$$

Equation (4) implicitly defines a rate of return to schooling in production. It can be applied to various groups of firms, such as firms located in different cities, or firms in different ownership classes. In the above approach we need to account for the possibility that observable or unobservable firm-specific factors affect the marginal-product ratio and may lead to over- or under- estimation of the effect of education on production.

In order to investigate this possibility, we use regression analysis. More specifically, We express equation (4) as

$$\frac{MPhed_i}{MPled_i} = (1 + r)^{sw_i} \cdot e_i \tag{3}$$

Where r is the expected return to schooling in production and e_i is an error term that captures other factors that may affect the MP ratio. Taking logs, we obtain the following approximation of a Mincer-type empirical model

$$\log\left(\frac{MPhed_i}{MPled_i}\right) = a + \log(1 + r)sw_i + e_i\,^*, \tag{4}$$

Equation (6) can easily be expanded to include experience as

$$\log\left(\frac{MPhed_i}{MPled_i}\right) = a + b \cdot sw_i + c \cdot ex_i + d \cdot ex_i^2 + e_i * \qquad (5)$$

where *b* is an estimate of *rc* and d allow us to calculate the effect of experience, and ex is the difference in average experience between highly educated and less educated workers. Because the ratio of marginal product only depends on the ratio of the two types of workers, not output, the advantage of this approach is that firm-specific effects (observed and unobserved, fixed or time-varying) related to output are canceled out. Therefore, it greatly reduces endogeneity problem in the estimation.[1]

[1] While a seemingly simpler approach is simply to regress marginal product on education, as can be seen in equation (2), this procedure would be subject to bias, because of correlation between omitted variables affecting output and marginal product that are also correlated with education. If they are not controlled for, the regression will be inconsistent.

E. Estimating the Indirect Effect of Education

The direct effect of education on production is estimated by incorporating measures of human capital inside the production function. However, education may also contribute to production indirectly, for example through better management or coordination within the firm, increasing a firm's total factor productivity and technical efficiency. In order to investigate this effect, we will estimate the effect of education on total factor productivity (TFP) and on technical efficiency.

TFP is measured by firm-specific efficiency and random productivity shock. It can be estimated either through the conventional production function or production frontier. For example, one possible model to estimate the effect of education on TFP is

$$\log(TFP_{it}) = \delta_0 + \delta_1 E_{pi} + \delta_2 E_{Si} + \delta_3 E_{ci} + \delta_4 E_j + v_i \qquad (8)$$

where E_p, E_s, E_c is the average years of education of production workers, technical workers, and the education of the CEO of the firm, respectively. In this case, δ1, δ2, δ3, measure the respective contributions of education to total factor productivity.

The technical efficiency of a given firm is defined as the ratio of observed output level to the corresponding stochastic frontier production level. Based on equations (3), (4), and (5), technical efficiency is

$$TE_i = e^{-u_i} \qquad (9)$$

Therefore, in this study, we can estimate the effect of education on a firm's technical efficiency simultaneously with estimation of the production frontier in a one-step approach.

3.2 Data

The data used to estimate the production functions are from a variety of sources and cover time periods from the 1980s through the year 2002. The long time period covered will permit us to track changes in regional inequality in social returns to schooling through much of the period of China's economic transformation. The contribution of labor types to output will be compared with wages and, where possible, nonwage income, to assess how well labor markets are working to allocate labor and skills and how labor-market efficiency has evolved since reform.

The data we have for estimation of the production functions include:

i) A survey 30 enterprises in the paper industry conducted in the early 1990 that covers the years 1985, 1987, and 1990.

ii) A survey of 442 urban SOEs, collectives, and some private enterprises in 24 cities of 12 provinces for the year 1991.

iii) A World Bank survey of production and innovation conducted by China's National Bureau of Statistics in 2001, which covers 1500 firms across ten service and manufacturing sectors and five cities over the period of 1998-2000. Five cities are Beijing, Shanghai, Tianjin, Chengdu and Guangzhou, representing different urban areas of diverse development level.

Surveys (i), (ii), and (iii) all include data on intermediate inputs, so both gross-value and value-added production functions can be estimated. Survey (i) contains data on worker schooling as well as occupation; Surveys (ii) contains data on worker occupational level only, thus we need assume average level of schooling for each occupation level to estimate private returns to schooling; and Survey (iii) contains data on worker occupation level and the average education level for different occupation levels. All three surveys report earnings data, particularly Survey (iii) has aggregate labor earnings data including wages, bonus and subsidies for three years, but only has one year (2000) disaggregated data for each occupational level.

Data for estimating the relationship between schooling and earnings comes from two sources:

i.) The Chinese Household Income Project (CHIP)

ii.) The Survey of the State and Life Chances in Urban China, 1949—1994 (LCUC). These data are currently in the possession of this research team. All three of these surveys have important information about family background and respondent schooling experience during the CR. The CHIP data provide income and earnings data for 1995 and 2002. For example, CHIP-95 data covered 6,928 urban households and

21,688 individuals located in Anhui, Beijing, Gansu, Guangdong, Henan, Hubei, Jiangsu, Liaoning, Shanxi, Sichuan and Yunnan provinces. The LCUC has earnings data for 1994 and a number of earlier years based on recall..

3.2. Preliminary Work

In order to explore the feasibility of our proposed research, we have carried out a preliminary empirical investigation some of which is described in detail in the appended paper. We have tentative estimates of the selection and sorting effects on the evolution of the private return to schooling for college graduates during China's reform between 1988 and 2002. We find evidence of substantial sorting gains under the traditional system, but gains have diminished and even become negative in the most recent data We take this as evidence consistent with the growing influence of private financial constraints on decisions to attend college as tuition costs have risen and the relative importance of government subsidies to higher education has declined. This evidence is consistent with the increasing importance of unmeasured financial constraints on college attendance and is the crux of our proposed research.

In this preliminary work on productivity effects of education, we have estimated returns to schooling in production from panel data of approximately 450 manufacturing firms in 5 major cities in China. The estimated marginal products dramatically exceed wages for both production and technical workers in both state-owned and foreign-invested enterprises, as shown in tables A and B below.

Table A. Total Factor Productivity and Marginal Products based on Production-Function Estimates and Average Annual Pay (Domestic SOE's)

City	Fixed-Effect Estimates (Average Annual Pay)			
	TFP	**Capital**	**Production Workers**	**Technical Workers**
Beijing	16.36	0.080	23.81 (9.32)	379.85 (13.32)
Chengdu	11.69	0.060	13.64 (7.26)	231.86 (12.74)
Guangzhou	21.54	0.097	32.23 (14.09)	888.71 (17.14)
Shanghai	21.18	0.131	22.93 (13.31)	740.82 (16.19)
Tianjin	13.74	0.083	22.93 (8.5)	258.21 (10.12)

Table B. Total Factor Productivity and Marginal Products based on Production-Function Estimates and Average Annual Pay (Foreign-Invested Firms)

City	Fixed-Effect Estimates (Average Annual Pay)			
	TFP	**Capital**	**Production Workers**	**Technical Workers**
Beijing	18.96	0.489	145.05 (14.16)	2,405.28 (38.57)
Chengdu	12.14	0.355	41.49 (9.70)	752.42 (30.40)
Guangzhou	16.43	0.761	76.17 (11.65)	1,616.60 (80.78)
Shanghai	20.72	0.736	452.54 (23.01)	3,933.17 (47.70)
Tianjin	15.29	0.783	87.06 (13.48)	1,260.00 (95.59)

The estimated direct returns to schooling in production (based on fixed-effect production function estimates) are substantial and possibly underestimated given the crude schooling data at our disposal, generally exceeding 20% after allowing for the "bricks and mortar" costs of education. These are shown in tables C and D.

Table C. Rate of Return Calculations from Fixed-Effect Estimates (Domestic SOE's)

	Equation 3 Return to Schooling (Production)	MP of Capital	Private Return (Wages)
Beijing	0.76	0.079	0.059
Chengdu	0.62	0.060	0.090
Guangzhou	0.77	0.097	0.019
Shanghai	0.73	0.13	0.017
Tianjin	0.52	0.083	0.014

Table D. Rate of Return Calculations from Fixed-Effect Estimates (Foreign-Invested Firms)

	Equation 3 Return to Schooling (Production)	MP of Capital	Private Return (Wages)
Beijing	0.64	0.49	0.19
Chengdu	0.16	0.36	0.06
Guangzhou	0.14	0.76	0.09
Shanghai	0.26	0.74	0.08
Tianjin	0.18	0.78	0.14

The estimation of the effect of average schooling per firm on firm TFP suggests an addition impact of about 6% increase in TFP per additional year of schooling, but accounts for only a small proportion of the FE production-function residuals.

Our preliminary research points to the need for further investigation as outlined in this proposal. Some of the puzzles that we hope to resolve are summarized as follows.

- The OLS return to college education increased between 1988 and 1995, but increased sharply between 1995 and 2002. In the year 2002, it remained somewhat small by international standards, approximately 7.1% per year of college. We plan to suggest reasons for this gap, which we suspect lies in the persistent underpayment of skilled workers in traditional enterprises in China.
- We will pursue the critical question of why sorting gains to college attendance have not only declined but become negative. The implications for educational funding policy are of the utmost importance.

- The vast gap between estimated marginal products and reported earnings revealed in our preliminary estimates will be investigated intensively. We plan to incorporate estimates of private returns based on enterprise-provided wage data with estimates based on data that are possibly more representative of the population at large.
- We will expand coverage of industry sectors to non-manufacturing enterprises.
- A major research question will be to establish a sound benchmark for the opportunity cost of investment in schooling.
- We will proceed further to investigate "external" effects of schooling operating through TFP at the firm- and city levels. To the extent that we identify TFP effects at the firm level, we need to investigate firm-level decision making and explore what entities may capture this residual effect of schooling on potential profit.
- Ultimately, a sample of enterprises encompassing a wider range of city sizes and a wider geographical dispersion, with a greater concentration of cities in the interior of China, would probably enable us to obtain more pronounced policy implications.

4. Research Team and Labor Allocation

Belton M Fleisher PI

Expertise: Belton Fleisher is Professor of Economics at Ohio State University He has authored and coauthored over 40 articles in professional journals including American Economic Review, Journal of Political Economy, the Review of Economics and Statistics, Journal of Comparative Economics, and China Economic Review and 7 books. Since 1990, his research has focused on economic growth, financial markets, and labor and productivity in the Chinese economy, and he has published over 20 articles on topics related to the Chinese economy. He has served on the executive committee of the Association of Comparative Economic Studies, and he is a co-editor of China Economic Review.

Major Task:

- Coordinate research of three co-PI's
- facilitate estimation of production functions with three data sets covering the 1980s and early 1990s.
- Primary responsibility for writing research reports.

James J Heckman Co-PI

Expertise: James J. Heckman is recipient of the Nobel Prize in Economic Science (2000).

- Adapt and specify econometric models of earnings functions to properly account for selection, selectivity, and funding-constraint issues.
- Adapt and specify econometric models of production functions to properly incorporate identifying instruments for endogenous inputs.
- Adapt and specify econometric models for production frontiers with special attention to appropriate maximum likelihood estimation under conditions of non-regularity.

Yifan Hu Co-PI

Expertise: Yifan Hu received her Ph.D in economics from Georgetown University in 2003. She has served as a consultant for the World Bank in Washington, D.C. and as research associate for the Institute for International Economics in Washington, D.C. She is currently research associate professor in the Hong Kong Institute of Economics and Business Strategy, School of Economics and Business, University of Hong Kong. She has authored and coauthored several papers on behavior of Chinese enterprises under evolving ownership structures.

Major Task:

- Facilitate estimation of production functions with World Bank survey conducted by China's National Bureau of Statistics in 2001, which covers 1500 firms across ten service and manufacturing sectors and five cities over the period of 1998-2000.
- Examine the effect of firm's skill structure on innovative capability.
- Investigate the relationship between return on education and marginal productivity.
- Participate in writing research reports.

Haizheng Li Co-PI

Expertise: Haizheng Li is associate professor of economics at the Georgia Institute of Technology. He received his Ph. D. in Economics from the University of Colorado at Boulder in 1997, where he specialized in econometrics and labor economics. His research focuses on applied econometrics, primarily in the areas of labor economics and industry studies, and he has published several articles in major journals on education, wage determination and labor supply in the Chinese economy. Li also conducts research on theoretical econometrics aimed at making advances in the semi-parametric estimation method for censored models. This research interest is particularly valuable for the proposed research.

Major Task**:**

- Work on methodology and estimations
- Work to obtain CUHS data
- Work with CHIP data and CUHS data
- Participate in writing research reports.

Xiaojun Wang Co-PI

Expertise: Xiaojun Wang is assistant professor in the department of economics, University of Hawaii at Manoa. He received his Ph.D. in economics from Ohio State

University in 2000. His research specialties are econometrics, macroeconomics, labor markets, and Chinese economy. He designs the econometric strategy for the semiparametric estimation of returns to schooling in our project.

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Shi Li Research Associate

Expertise: Shi Li is professor in the Institute of Economics, Chinese Academy of Social Sciences in Beijing. He received his M.A. in economics from Beijing University in 1984. He is head of the project on Income Inequality and Social Policy in China and is an expert on the Chinese Household Income Project. He supervises our estimation of returns to schooling based on the 2002 CHIP data.

Heng-fu Zou Research Coordinator

Expertise: Heng-fu Zou is a senior research economist in the Development Research Group at the World Bank. He received his Ph.D. in economics from Harvard University in 1989. His research specialties are economic growth, public expenditure, fiscal federalism, and income distribution.

5. Time Framework and Budget

I. Time frame:

The project is scheduled to be completed in three years, starting from 1 January, 2006. The deliverables are listed as follows.

1 August 2005 – 31 December, 2006):

- A research paper on the effect of education on individual's productivity based on conventional production function estimation
- A research paper on the trend of the effect of education on individual earnings using multiple year data, focusing on the extent to which individuals who attend college have sorted efficiently on the basis of their returns to schooling.
- A report of the effect of education on production and personal income
- A report on China's human capital policy and policy recommendations on reducing inequality

Project Completion Date: 31 December, 2006.

II. Budget Plan

Year 1: Total $73,000

A. PI's:

- Belton Fleisher ($25,500)
  - Summer support (1 month), $12,000
  - Trip to China, $4,000
  - Conference trip: $2,000
  - Research Assistant 7,500

- James Heckman ($16,000)
  - Research Assistance and travel support.

- Yifan Hu ($7,000)
  - Field trip/traveling : $4,000
  - Conferences: $3,000
- Haizheng Li ($13,500)
  - Summer support (1 month), $10,000
  - Conferences and Trip to China, $2,500
  - Research assistant: $1,000
- Xiaojun Wang ($7,000)
  - Summer Support ($4000)
  - Trip to mainland to coordinate with Fleisher and Li ($3000)

B. Research Associate

- Shi Li ($4,000) Trip to U. S. to coordinate with Fleisher and Li

Table 1. Higher Education and Economic Growth Rates for Selected Countries

Country	Gross Enrollment Ratio in Higher Education (%)[b]	
	1980	1993
China	1	2
India	4	8
Korea (Republic)	16	51
Malaysia	4	7
Thailand	13	19
Hong Kong	5	20
Japan	29	32
Former USSR	22	45
United States	56	72

Source: World Bank (1997), p.6
Notes:
[a]Figure in parentheses is for 1978-91 and is modified to account for over reporting. See Wang and Meng (2001).
[b]Gross enrollment ratio is the number of all postsecondary students divided by university-going age group. The second column contains data for the 1993 or for the following dates: India 1992, Hong Kong 1991, United States 1990.
[c] This represents spending on all education levels.

Table 2. Public Expenditures on Education as a Percentage of GNP in 1995

World	5.2
China	2.5
Philippines	3
Thailand	4.1
India	3.3
Malaysia	4.7
Singapore	3
Pakistan	2.8
Turkey	2.2
South Korea	3.7
Egypt	4.8
Mexico	4.9
Brazil	5.1
Argentina	3.8*
United States	5.4*
Japan	3.6*
Canada	6.9*
Germany	4.8
Russian Federation	3.5
Poland	5.2
Hungary	5.3

* Data was only available for 1994

Source: UNESCO, 1999

Table 3. Investment in Educational Expenditures at All Levels of Government
(In 100 Million of Yuan)

Year	Government Appropriations for Education	GDP	Educational Expenditure As Percentage of GDP
1991	618	21,618	2.9%
1992	729	26,638	2.7%
1993	868	34,634	2.5%
1994	1175	46,759	2.5%
1995	1412	58,478	2.4%
1996	1672	67,885	2.5%
1997	1863	74,463	2.5%
1998	2032	78,345	2.6%
1999	2287	82,068	2.8%
2000	2563	89,468	2.9%
2001	3057	97,315	3.1%

Source: China Statistics Yearbook 2003

Table 4. Gross Enrollment Rate of Schools Age 18-22 %

Year	Enrollment Rate
1990	3.4
1991	3.5
1992	3.9
1993	5
1994	6
1995	7.2
1996	8.3
1997	9.1
1998	9.8
1999	10.5
2000	12.5
2001	13.3

Source: China Educational Finance Statistical Yearbook, 2002.
Notes: The gross enrollment rate of schools by level is defined as the total enrollment of a school level divided by the total population within the age range for a given school level, which is then multiplied by 100. Junior secondary schools include secondary schools and vocational secondary schools.

Table 5. Per Pupil Expenditure By Region

(In 2001 Yuan)

Region	1998	1999	2000	2001
Beijing	4,973	6,347	7,910	10,098
Tianjin	1,936	2,163	2,530	3,042
Hebei	586	658	722	856
Shanxi	675	747	794	996
Inner Mongolia	926	1,063	1,106	1,399
Liaoning	1,217	1,340	1,456	1,627
Jilin	1,170	1,303	1,378	1,695
Heilongjiang	1,052	1,265	1,348	1,688
Shanghai	4,557	5,331	6,333	6,805
Jiangsu	1,151	1,296	1,360	1,474
Zhejiang	1,255	1,497	1,647	2,142
Anhui	554	612	603	705
Fujian	866	1,018	1,163	1,377
Jiangxi	522	567	620	793
Shandong	758	862	984	1,155
Henan	476	520	567	678
Hubei	683	756	831	993
Hunan	580	675	722	857
Guangdong	1,085	1,157	1,286	1,468
Guangxi	555	618	675	836
Hainan	771	890	885	1,046
Chongqing	749	793	855	1,033
Sichuan	639	697	751	918

Guizhou	428	500	561	672
Yunnan	960	1,044	1,101	1,281
Tibet	1,612	2,044	2,004	2,385
Shaanxi	663	761	808	1,040
Gansu	682	801	832	982
Qinghai	1,098	1,175	1,335	1,645
Ningxia	853	965	1,037	1,350
Xinjiang	1,225	1,319	1,412	1,859

Source: Author's calculation from China Statistical Yearbook 1999-2003

Table 6. Percent of Population By Level of Education and Region

Region:	Population (Age 6 and Over, Thousands)	Fraction Within Each Province				
		Illiterate	Primary Education	Junior Secondary School	Senior Secondary School	College or Higher Level
Beijing	13239	4.99	14.86	35.67	23.99	20.49
Tianjin	9522	6.36	23.16	37.36	22.57	10.57
Hebei	62588	6.80	34.41	42.50	11.61	4.69
Shanxi	30192	5.66	31.63	45.41	12.67	4.63
Inner Mongolia	22236	11.93	29.70	37.82	14.91	5.64
Liaoning	39676	4.96	29.75	46.68	13.09	5.52
Jilio	25500	4.33	32.23	39.78	17.16	6.50
Heilongjiang	36007	6.12	31.07	43.24	14.71	4.87
Shanghai	15469	7.64	17.50	34.70	25.10	15.07
Jiangsu	69427	12.39	31.96	38.69	13.14	3.83
Zhejiang	43244	12.21	34.23	34.54	13.25	5.77
Anbui	58813	14.66	36.65	38.66	7.39	2.64
Fujian	32162	11.89	38.72	32.04	13.15	4.20
Jiangxi	38249	9.10	41.68	34.83	11.48	2.91
Shandong	83881	10.10	28.06	41.76	14.42	5.67
Henan	88118	7.76	29.51	46.47	11.97	4.30
Hubei	56354	12.41	39.25	32.25	12.23	3.86
Hunan	61435	7.23	37.26	38.69	12.47	4.35
Guangdong	71705	6.41	36.83	37.78	13.84	5.15
Guangxi	44120	8.60	39.57	37.03	11.32	3.48
Hainan	7273	7.88	34.55	39.35	14.62	3.59

Chongqing	28823	9.31	42.33	34.63	10.38	3.35
Sichuan	79863	12.24	39.58	33.99	10.44	3.75
Guizhou	34146	16.21	42.71	30.03	7.54	3.52
Yunnan	38413	20.30	46.15	25.19	6.37	1.99
Tibet	2406	37.99	46.63	11.72	2.87	0.79
Shaanxi	34241	13.03	35.43	34.59	12.99	3.95
Gansu	23833	18.11	38.36	28.86	11.61	3.05
Qinghai	4724	22.25	38.02	27.65	8.95	3.15
Ningxia	5068	14.98	33.82	33.60	11.94	5.66
Xinjiang	18220	7.74	35.80	31.73	14.85	9.88
National Total	1,178,951	10.23%	34.96%	37.65%	12.45%	4.71%

Note: The data in this table are obtained from the Sample Survey on Population Changes in 2002. The sampling fraction is 0.988%.

Table 7. Per Pupil Expenditure By Region
(In 2001 Yuan)

Region	1998	1999	2000	2001
Beijing	4,973	6,347	7,910	10,098
Tianjin	1,936	2,163	2,530	3,042
Hebei	586	658	722	856
Shanxi	675	747	794	996
Inner Mongolia	926	1,063	1,106	1,399
Liaoning	1,217	1,340	1,456	1,627
Jilin	1,170	1,303	1,378	1,695
Heilongjiang	1,052	1,265	1,348	1,688
Shanghai	4,557	5,331	6,333	6,805
Jiangsu	1,151	1,296	1,360	1,474
Zhejiang	1,255	1,497	1,647	2,142
Anhui	554	612	603	705
Fujian	866	1,018	1,163	1,377
Jiangxi	522	567	620	793
Shandong	758	862	984	1,155
Henan	476	520	567	678
Hubei	683	756	831	993
Hunan	580	675	722	857
Guangdong	1,085	1,157	1,286	1,468
Guangxi	555	618	675	836
Hainan	771	890	885	1,046
Chongqing	749	793	855	1,033
Sichuan	639	697	751	918

Guizhou	428	500	561	672
Yunnan	960	1,044	1,101	1,281
Tibet	1,612	2,044	2,004	2,385
Shaanxi	663	761	808	1,040
Gansu	682	801	832	982
Qinghai	1,098	1,175	1,335	1,645
Ningxia	853	965	1,037	1,350
Xinjiang	1,225	1,319	1,412	1,859

Source: Author's calculation from China Statistical Yearbook 1999-2003

Table 8. Government Education Appropriations as a Percent of GDP

Region:	1998	1999	2000	2001
Beijing	5.403	6.213	6.851	7.594
Tianjin	2.576	2.607	2.629	2.907
Hebei	2.074	2.143	2.101	2.173
Shanxi	2.971	3.283	3.332	3.871
Inner Mongolia	3.172	3.350	3.184	3.615
Liaoning	2.203	2.219	2.199	2.247
Jilin	3.638	3.697	3.555	3.683
Heilongjiang	2.416	2.724	2.570	2.818
Shanghai	2.880	3.002	3.157	3.098
Jiangsu	2.115	2.205	2.122	2.091
Zhejiang	1.844	2.073	2.120	2.541
Anhui	2.238	2.418	2.379	2.659
Fujian	1.929	2.072	2.148	2.314
Jiangxi	2.191	2.373	2.430	2.822
Shandong	1.874	1.935	1.980	2.022
Henan	2.181	2.270	2.240	2.387
Hubei	2.154	2.265	2.266	2.446
Hunan	2.282	2.407	2.323	2.504
Guangdong	2.175	2.207	2.233	2.411
Guangxi	2.808	2.951	3.073	3.507
Hainan	2.813	3.033	2.822	3.165
Chongqing	2.501	2.616	2.771	3.091
Sichuan	2.426	2.606	2.702	3.026
Guizhou	3.517	3.820	4.140	4.671

Yunnan	3.799	4.070	4.233	4.705
Tibet	6.412	7.017	6.566	6.916
Shaanxi	3.756	4.073	4.023	4.689
Gansu	3.644	4.133	4.322	4.857
Qinghai	3.858	3.893	4.182	4.649
Ningxia	3.933	4.233	4.356	5.114
Xinjiang	4.174	4.399	4.190	5.182

Source: Author's Calculation from China Statistical Yearbook 1999 - 2003

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[i] *Econometrica* 66, 5 (Sept. 1998): 1017-1098.

[ii] These derivatives include average treatment effect (ATE), treatment on the treated (TT), treatment on the untreated (TUT), bias, selection bias, and sorting gain.

[iii] Fan (1992): *Journal of the American Statistical Association* 87: 998-1004. Fan (1993): *The Annals of Statistics* 21: 196-216.

[iv] This approximates the rule-of-thumb bandwidth selector proposed in Fan and Gilbels (1996).