Economic Transition, Higher Education and Worker Productivity in China*

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Abstract

In this study, we investigate the role of education on worker productivity using firm level panel data from China. We first estimate marginal products of workers in different education classes and evaluate the direct impact of schooling on marginal products. We also assess the indirect effect of schooling on firms' total factor productivity. We find that estimated marginal products are much higher than wages, and the gap is larger for highly educated workers. The return to education is much higher when estimated in terms of product than when it is estimated in terms of earnings. For the overall sample, an additional year of schooling raises marginal product by 18.3-24.5%. Estimates vary substantially across ownership types and regions. The estimated effect of schooling is highest in foreign-invested firms and in cities that are more economically advanced. In addition to its direct effect on production, education is estimated to have positive and significant effect on TFP growth for non-SOE domestic firms.

JEL Codes O15, P23, J31

1. Introduction

Education is a central issue in China's long term strategy to promote increased standards of living and to reduce inequality. Fleisher and Chen (1997) find that China's high and rising regional income inequality reflects a wide, and perhaps growing, gap in labor and total-factor productivity which, in turn, they attribute to regional inequality of investment in higher education. Evidence of underinvestment in human capital in China, particularly in higher-education end, has been corroborated by Fleisher and Wang (2001a, 2003, 2004). Heckman (2005) shows that expenditure on higher education in China is characterized by extreme regional inequality and that there is a serious imbalance between investment in physical and human capital. At the micro-level, little is known about how education affects production and productivity in Chinese economy where labor markets are frequently segmented and where the transition from soft budget constraints is incomplete.

There is considerable evidence from estimation of Mincerian models that returns to schooling in China have increased in the past 15 years from far below world averages and now approach those observed in major market economies (Zhang, Zhao, Park, and Song, 2005, Li, 2003, Li & Luo 2004, Yang, 2002).[1] However, we cannot infer that these changes in relative wages by skill level closely reflect changes in relative marginal products, because there remain many distortions inherited from the system of central planning and rigid allocation of labor from the top. Not only has the transition from planning varied across firms by ownership type, i.e., state-owned, foreign involved, domestic private firms, but also by geography, with the coastal region having proceeded much further toward uncontrolled markets than has the interior and western region.

In this paper we present estimates of the effects of human capital in production using a panel of firm-level observations. Our method allows us the advantage of avoiding the assumption that wage rates closely approximate the marginal product of

[1] Some recent studies have used more sophisticated econometric techniques to measure policy relevant effects of education in China based on earnings, such as the treatment effect of treated and treatment effect on the untreated, in addition to the average treatment effect (Heckman and Li 2002, Fleisher, Li, and Li and Wang 2006).

labor. Moreover, by comparing the marginal products of workers with different amounts of education in our panel data we can exploit the advantages of both “differencing” and fixed-effect (FE) estimation. Thus, the bias in estimating the effect of schooling on productivity which would result from omitted unobserved firm characteristics (including worker characteristics correlated with the firm) should be sharply reduced if not eliminated.[2]

Finally, we compare estimated productivity and the impact of human capital on production across ownership types and geographical regions. These comparisons shed light on how the decline of the state sector and other aspects of transition and economic development contribute to productivity growth. While it is generally believed that transition to a market system will raise productivity (e.g., Brown et al., 2006), the mechanisms within firms that channel market forces to production are not well known. In this study, we can provide some insight about the human capital channel.

We proceed as follows. First we specify a value-added production function in which the inputs include capital and labor divided into highly-educated and less-educated workers. Next we derive the marginal products of the two types of production workers from the estimated production-function parameters. Then we use information on average schooling level of highly-educated and less-educated workers to estimate the impact of schooling on marginal products and derive the rate of return to schooling in production. We compare the rate of return in production to that reflected in relative wages of workers with more or less schooling. We also estimate the impact of worker- and CEO-schooling on firms’ total factor productivity (TFP).

The rest of the paper is organized as follows. Section 2 discusses methodology. Section 3 describes data and variables. In Section 4, we discuss our estimates of the marginal products of highly educated and less educated workers. In sections 5 and 6, we

[2] Hellerstein, Neumark, and Troske (1999) jointly estimate wage and production functions for a sample of United States firms and are thus able to directly compare the effects of schooling, gender, and other worker characteristics on marginal product and wages. Unfortunately our data do not permit us to take this innovative approach.

estimate the effect of education on marginal product and on total factor productivity, respectively. Section 7 concludes.

2. Methodology

Our first step is to obtain estimates of the production elasticities of inputs of interest. We specify the following Cobb-Douglas value-added production function

$$Y_{it} = A_{it} K_{it}^{\beta_{kj}} L_{sit}^{\beta_{sj}} L_{pit}^{\beta_{pj}} e^{u_{it}} , \qquad (1)$$

where Y is output, K is capital, L_s is the number of highly educated workers, L_p is the number of workers with less education, u is a disturbance term for firms i= 1, 2, …, n from year t=1, 2, …, T, and j indicates cities (or ownership sectors). The parameters β_k, β_p, and β_s are the output elasticities of the corresponding inputs.

This specification reflects overwhelming evidence in the human-capital literature that earnings are affected by education, presumably because education raises productivity. It also reflects our assumption that firms group workers according to their acquired skills and schooling into occupational categories that are not perfectly substitutable in production. Similar specification can be found in the literature. For example, Pavcnik (2002) includes the number of skilled labor and unskilled workers in the production function for Chilean manufacturing plants. Moretti (2004a and 2004b) investigates the spillover effects of human capital in United States cities using plant level data, and he specifies the production function to include number of hours worked by skilled workers and unskilled workers. Fleisher and Wang (2001a, 2004) specify a production function for Chinese enterprises in which labor is measured by the number of workers in different occupations. In the production functions specified by Hellerstein, Neumark, and Troske (1999), workers are distinguished by different demographic characteristics including education.[3]

[3] We use the Cobb-Douglas functional form here for simplicity as commonly found in the literature. In our estimation, we are unable to reject this functional form in favor of a translog specification.

Although we argue that it is appropriate to disaggregate labor by schooling level inside the production function, we also recognize that the educational level of a firm's workforce and that of its top management may help to develop and adapt to new technology, and then to increase firm TFP. Thus in this study we investigate both the direct effect of education on production through its embodiment in labor and its effect on TFP through the average level of schooling of a firm's workforce and the level of schooling of its top management. We believe that this is a way to gain some insight into the channels through which schooling plays a role in TFP growth through the spread of technology and management methods.[4]

Taking the log of both sides of equation (1), we obtain our empirical model. The estimated input elasticities lead directly to derivation of the inputs' marginal products. The marginal product of highly educated and less educated workers, respectively, for firm i at year t (for city or sector j) are

$$MP_{s_{it}} = \hat{\beta}_{sj} \frac{Y_{it}}{L_{s_{it}}} \quad \text{and} \qquad (2)$$
$$MP_{p_{it}} = \hat{\beta}_{pj} \frac{Y_{it}}{L_{p_{it}}}$$

Define the effect of education on marginal product as an annual rate of return r_i, i.e., an additional year of schooling raises the marginal product by r_i. We quantify the effect of education on production by assuming that less educated workers can be converted to highly educated workers through giving them a sufficient number of years of schooling. Suppose *sw* is 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. Then, under the simplifying assumption that the difference in marginal product in a firm is only resulted from the educational difference, we get (we suppress subscript t

$$MP_{s_i} = (1 + r_i)^{sw_i} MP_{p_i}, \qquad (3)$$

[4] Our access to information on schooling only inside the firm limits our ability to evaluate the external effects of schooling on production as, for example, in Moretti (2004a, 2004b).

or

$$\frac{MP_{s_i}}{MP_{p_i}} = (1+r_i)^{sw_i} \tag{4}$$

Equation (4) implicitly defines a rate of return to schooling in production for workers in each firm i at time t.[5]

A problem in obtaining unbiased estimates of the rate of return based on equation (4) is in the influence of firm-specific factors other than education. Such influences on relative marginal products might include firms' location, ownership type, product characteristics, workers' non-educational characteristics, and other observable or unobservable firm-specific factors. Assume that the effect of education in terms of annual return based on marginal product is *r*; and inter-firm differences in marginal product between highly educated and less educated workers are also caused by factors other than education. Then we transform equation (4) into a stochastic specification,

$$\frac{MP_{s_i}}{MP_{p_i}} = (1+r)^{sw_i} \cdot e_i \tag{5}$$

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

$$\log\left(\frac{MP_{s_i}}{MP_{p_i}}\right) = \alpha_i + \log(1+r) sw_i + e_i^* . \tag{6}$$

Equation (6) can be expanded to include control variables like experience as

$$\log\left(\frac{MP_{s_i}}{MP_{p_i}}\right) = a_i + b \cdot sw_i + c \cdot ex_i + d \cdot ex_i^2 + e_i^* \tag{7}$$

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[5] Notice that the marginal product ratio $\frac{MP_{s_i}}{MP_{p_i}}$ expands to $\frac{\hat{\beta}_{sj} \frac{Y_i}{L_{s_i}}}{\hat{\beta}_{pj} \frac{Y_i}{L_{p_i}}} = \frac{\hat{\beta}_{sj} L_{p_i}}{\hat{\beta}_{pj} L_{s_i}}$, implying that firms choose workers based on their MP via hiring some specific numbers of workers with different education.

where b is an estimate of r, c 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. Based the Mincer-type human capital model, on-the-job-training (with experience as a proxy) is another way (in contrast to schooling) to accumulate human capital, which may contribute to higher marginal product.

The left-hand side of equation (7) is the log-difference in marginal product between highly-educated and less-educated workers. A big advantage of this specification is that it allows us to difference out observed/unobserved time-varying and time-invariant variables that affect MP. More specifically, suppose the marginal product of labor is affected by the amount of human capital measured by education and experience, as well as by many other observed/unobserved firm specific characteristics Z_{it}, such as technology, capital, output, etc. The firm-specific characteristics may be time-varying or invariant, and some of them may be correlated with education level of workers. For example, they may affect a firm's education requirement on hiring and thus are correlated with education level of the workers.[6] For such time-varying endogenous variables, panel data estimation alone cannot help. However, within a particular firm, Z_{it} is invariant across worker groups. For example, workers may have different marginal product, education and experience, but they face the same firm-level capital, technology, etc. Thus, in estimating equation (7), Z_{it} will be differenced out. Therefore, such an empirical specification largely if not all mitigates the potential endogeneity problem.[7]

Equation (7) will be estimated using fixed-effects regression. The specification of equation (7) plus fixed-effects estimation has the additional advantage that it can reduce or avoid omitted ability bias. It is well-known that the omitted ability bias is a big problem in estimating the effect of schooling using individual's earnings because of the correlation between omitted ability and schooling level. In our equation (7), omitted

[6] As a result, the estimation by regressing marginal product of each class of workers on their education will be inconsistent.
[7] Another advantage of this approach is that the firm specific markups are also differenced out in estimating the effect of education. This is a common problem when measure a firm's productivity based on the value of output rather than physical units of the output, because it is difficult to distinguish true productivity and the firm specific markups. It also removes the effect due to wage differentials caused by local living costs.

ability bias may also be present for the same reason, because marginal product may be affected by unobserved ability and the ability should be correlated with education. In the Mincer-type earnings equation, the omitted bias problem cannot be resolved with panel data, as FE estimation cannot be applied because an individual's schooling normally does not change after the person enters the labor market. Thus, schooling will be perfectly collinear with individual fixed effects. In our procedure, however, average education does change across years because of worker turnover. Then, in FE estimation, the omitted ability that is firm-specific will be differenced out, assuming that the average ability difference between highly educated and less educated workers stays constant over year. This is why the combination of the log-difference specification plus the panel nature of our data allows us to control for time-varying or -invariant omitted variables in the estimation. This "difference-in-difference" type estimation will generate a consistent estimate of the rate of return to education in terms of marginal product.[8]

The next step is to estimate the indirect effect of education, i.e., the effect of education on total factor productivity (TFP).[9] In the vast literature on economic growth, human capital has generally been recognized as a critical contributor to economic growth and the growth of total factor productivity (Lucas, 1988). As Benhabib and Spiegel (1994) show, education can facilitate the development and adaptation of new technology. Education facilitates spillovers, externalities, and endogenous skill-based technical changes (Acemoglu 1996, 1998). Additionally, the sharing of knowledge and skills through formal and informal interaction between educated and uneducated workers may generate positive externalities across workers and thus makes the firm more productive (Moretti 2004a).

At the micro-level, however, little is known about the indirect effect of education within a firm on its TFP. For example, the average education of workers within a firm

[8] This is not to be confused with the standard difference-in-difference estimator. In our case, we first difference the marginal product between two classes of workers and then difference from the time mean in the fixed effects estimation.

[9] An alternative approach is to incorporate the firm education measure in technology term of the production function to do one-step estimation. We adopt the two-step estimation here to avoid the collinearity between firm's education measure and the number of workers in each education class.

may help to adopt new technology and thus increase productivity through the interaction between well-educated and less-educated workers. Our paper investigates the indirect effect of education on productivity in TFP regressions.

3. Data and Variables

Our data are derived from a firm-level survey conducted by the World Bank. The World Bank's sample covers 998 manufacturing firms selected in five cities and five manufacturing industries over the period of 1998-2000. The five cities are Beijing, Shanghai, Guangzhou, and Tianjin on the coast of China, and Chengdu the provincial capital of southwest Sichuan. The five industries are all in manufacturing: apparel and leather goods, consumer goods (mainly household appliances and consumer durables), electronic equipment, electronic components, and vehicles and vehicle parts. The sample is randomly selected from all firms in their respective cities/industries and the size range is extreme, with the reported number of production workers ranging from 1 to over 55,000. In order to reduce the influence of extreme outliers, we confine our research to the sub-sample with at least 100 total workers, at least five of whom have schooling at the level of bachelor degree or above. As a result, there remain 446 enterprises in our sample.

The data contains a broad variety of firm-level characteristics pertaining to measures of output, workers' schooling level, age, and wages. Detailed information on the variables is presented in Table 1. Four variables – value-added, capital stock and the number of two categories of employees are used in the production function estimation. Value added is defined as sales less intermediate goods and adjusted for final- and intermediate-goods inventory changes. Capital is the book value of total fixed assets. Nominal variables are not deflated, but year dummies are included in all regressions to act as deflators. As implied above, the variance of output and inputs across the firms is large.

The two employee categories are (i) highly educated (L_s) and (ii) less educated workers (L_p).[10] In the survey, each firm is asked to provide information on the average education level for its full time employees across different occupations.[11] Using the schooling code for each type of worker, we denote the employees in each occupation level as either highly educated or less educated. The highly educated group mainly consists of engineering, technical personnel, and managerial personnel (including sales); and the less educated group mainly consists of basic and auxiliary production workers.[12] In our sample, each firm on average has 203 highly educated workers with average 16.7 schooling years and 677 less educated workers with 10.8 schooling years.[13]

The survey also contains information on the total labor cost for each occupational group, but the data is available for the year 2000 only. We estimate the annual earnings per employee in 2000 for each occupational group, using the total labor cost of that group dived by the number of workers in the group. The estimated annual earnings include all compensations such as wages, bonus, subsidies and other items. As shown in Table 1, the average annual earnings for the workers with high and less education are 96,300 and 36,490 yuan RMB, respectively.

Following the literature, we use job experience as a proxy for on-the-job training. We construct a variable representing average experience for the two educational groups, defined as the difference between average age and average schooling and subtract 6. The average experience for highly educated and less educated workers is 12.71 and 14.39 years respectively in our sample. We group the firms into three ownership categories:

[10] In China, it generally takes 6 years to finish primary school, 9 years for junior high school, 12 years for senior high school, 16 years for bachelor degree, 19 years for master degree and 21 years for a doctor degree.

[11] The education level is recorded from values 1 to 7, where 7 represents no education, 6 is primary school, 5 is junior high school, 4 is senior high school, 3 is university/college, 2 is master degree and 1 is doctor degree. Based on the Chinese education system, we assume 6 years for primary school, 3 years for junior high school, 3 years for senior high school, 4 years for college, and 3 years for graduate. We define highly educated workers to be those employees who typically have a bachelor degree or above, that is, with 16 or more schooling years; while less educated workers are those who typically have less than 16 schooling years.

[12] We exclude service personnel and other workers in the production function because they do not belong to any category related to production.

[13] The average years of schooling are calculated using average education of each occupational group weighted by the share of workers in that group.

state-owned enterprises (SOE), foreign-involved enterprises (FIE, joint-ventures or wholly foreign owned firms), and Non-SOE domestic enterprises (NDE, all other firms).

4. Marginal Product of Highly Educated and Less Educated Workers

Estimation of production functions is subject to bias from omitted firm-specific effects correlated with the regressors (Tybout, 2000). In order to avoid this omitted-variable problem, we apply two-way fixed effects estimation using both firm- and year-dummy variables to control for firm- and year-specific fixed effects. The estimates of the production function are presented in Table 2. When we tested the Cobb-Douglas (C-D) estimates against estimates based on the more general translog specification, we were unable to reject C-D. The F-value for this test is 1.41 and the p-value is 0.21. Therefore, we use only the C-D estimation results. Column 1 shows estimation results for the basic specification, and columns, 2, 3, and 4 show results based on specifications in which we include interaction terms between year dummies and city dummies or between year dummies and ownership sector dummies in order to capture possible time-varying and city or sector specific factors that might be correlated with both output and with production inputs.

The results are very robust across specifications.[14] The estimated elasticities of capital and both labor inputs are all statistically significant at conventional levels. The estimated elasticities imply that the sample firms operate under increasing returns to scale.[15] The estimated coefficients of the year dummies imply that total factor productivity increased over the sample period. The capital elasticity and that of less educated workers are both in the range of 0.34-0.37; while the elasticity of highly educated workers is much larger, in the range of 0.49-0.54. The finding of higher elasticity of highly-educated workers relative to less-educated workers is consistent with other studies. For example, in her production function estimation using plant level panel data from Chile, Pavcnik (2002) also finds a higher elasticity for skilled labor than for

[14] The estimation results are insensitive to stratification by industry sub-sector.
[15] We test for constant returns to scale, and the null hypothesis of constant returns to scale is rejected.

unskilled labor based on both fixed effects estimation and semi-parametric estimation for machinery and chemical industries. Moretti (2004a and 2004b) also finds a higher elasticity of hours worked by skilled workers using United States plant level data in 1982 and 1992.

We have used fixed-effect estimation in order to control for time-invariant, firm-specific omitted variables and for year-specific factors common to all firms. However, some omitted time-varying variables specific to individual firms may still lead to endogeneity bias in our estimates. This problem is especially likely to affect estimated labor elasticities, because the cost of adjusting labor inputs, particularly unskilled labor is relatively low. Often, this problem is ignored in the literature due to the difficulty of finding instruments.[16] However, in out data set, there are a few variables that can be used as instruments for instrumental variable (IV) estimation. We try to identify supply side variables that may be correlated with firms' hiring decisions but not to firm-specific technology or firm-specific demand shocks. Such variables can come from supply-side shocks to local labor markets.[17] There are four such variables: 1) the number of applicants for each high-education job; 2) the number of applicants for each low-education job; 3) the average number of weeks to fill the last high-education job; and 4) the number of weeks to fill the last the low-education job. These variables have been reported for one year only, 2000. Thus we cannot perform fixed-effect estimation in conjunction with the IV estimation.[18] Given the possibility of reporting errors, we run IV regression using a robust method which down-weights the sample outliers to make the estimation less sensitive to measurement errors.[19]

Table 2a shows the results of IV estimation of equation (1). The adjusted R-square of the first stage regression is in the neighborhood of 0.5, which suggests that we

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[16] In a recent study, Pavcnak (2002) uses semi-parametric estimation developed in Olley and Pakes (1996) to account for unobserved firm endogeneity in estimating firm production functions.

[17] Blundell and Bond (1998) propose a GMM type estimation using moment conditions based on lagged difference of explanatory variables as instruments in production function estimation.

[18] Based on the phrase of the question in the survey, it is unclear which year those instrument variables are referred to. We just simply assume that they are the same across years and run a pooled IV estimation. Due to many missing values for instrumental variables, the sample size becomes much smaller.

[19] The robust procedure is available in Stata. For details, see Huber (1964), for example.

are using reasonably "strong" instruments. We also test the validity of the instruments by the over-identifying restriction test of Davidson and MacKinnon (1993). The p-value for the test is 0.979, and thus does not reject the null that the over-identifying instruments are valid given the validity of a subset of the instruments that identifies the model. The IV results in Table 2a are generally consistent with those in Table 2, although magnitudes of the estimated parameters differ slightly.[20] We use the fixed effects estimates in our subsequent analysis because they are based on the full three years of panel data.

The marginal products (MP) calculated from the FE estimates of equation (2) are shown in Table 3a.[21] Tables 3b and 3c report calculations of MP for each city and ownership type, also based on the FE estimates shown in Table 2.[22] The marginal product of capital can be interpreted as the marginal rate of return to investment in physical capital gross of depreciation. The mean marginal product of capital across individual firms is 165% with an immense range between minimum and maximum. It also varies widely across aggregations by location and ownership type. In the cross-city level of aggregation (Table 3b), the lowest return to capital is in the interior city of Chengdu (84.8%) and the highest in Shanghai (222%), followed by Beijing and Guangzhou, with Tianjin in fourth place.

An important policy of the Chinese government to address growing regional inequality is its "Go-West" program, which emphasizes capital investment in western areas.[23] Even though our estimates of the MP of capital are very high in all regions, it is lowest by a large margin in the Western city of Chengdu. An implication would be that raising the MP of capital through improving infrastructure and fostering technology transfer through foreign direct investment in lagging regions should be at least as

[20] The similarity of IV estimates and FE estimates indicates that time-invariant factors may dominate the unobservable in the model. This is reasonable for the three-year time span of our data. Thus, FE estimation can largely remove the endogeneity problem in the production function estimation.

[21] We use the estimates from Model 1 for the subsequent analyses, as it is the most parsimonious model.

[22] One alternative is to estimate the production function separately for cities or ownership sectors. For the consideration of degree of freedom, we use the production estimated based on the full sample to calculate marginal product.

[23] The Chinese "Grand Western Development" Project launched in 2000 encompasses two million square miles and 300 million people spread across eleven provinces and autonomous regions. China views it a crucial plan for reducing regional gap.

important consideration as subsidizing capital growth within firms. This is a topic worth further investigation (Démurger, Sachs, Woo, Bao, and Chang, 2002; Démurger, 2001, Fleisher, Li, and Zhao, 2005). Aggregating across by ownership types (Table 3c), non-SOE domestic firms have the highest marginal product of capital, while SOEs have the lowest, about one eighth that in non-SOE domestic ownership group. One explanation for this gap is that non-SOE domestic firms face borrowing constraints, while SOEs have faced softer budget constraints reflected in easier access to loanable funds.

In Table 3a we see that the marginal product of highly educated exceeds that of less educated workers by a large margin. Across cities (Table 3b), the MP of labor varies widely from east to west, as does the MP of capital. The implications for regional inequality are at least as important as are the implications of regional variation in the MP of capital, discussed above. Shanghai shows the highest MP for both classes of workers, while Chengdu has the lowest with a MP of highly educated workers only 23% that of Shanghai. For less educated workers, Shanghai tops Chengdu by a factor of 7.7. Among ownership groups, the foreign involved sector has the highest MP of both classes of workers, while the SOE group has the lowest (Table 3c). The ratio of MP of highly educated workers to that of less educated workers is 5.8 in the foreign-involved sector and 5.5 among SOEs.

In almost all cases, workers are paid less than their marginal products.[24] In Table 3a, in year 2000, MPs is about 12.9 times the wage of highly educated workers; and about 7.5 times of the wage of less educated workers. In Table 3b we see that Shanghai has the highest MP-wage gap, followed by Guangzhou. For Shanghai, the ratio of MP to wage is about 69.2 for highly educated workers and 33.5 for less educated workers. The ratio for Beijing is the lowest. Across ownership groups (Table 3c), foreign involved

[24] As mentioned in the footnote for Table 1, the maximum of average earnings is unreasonably high, which indicates that wages might be overestimated. Therefore, the gap between marginal revenue product and wages discussed here may be an underestimate.

firms have the highest gap, with the ratio of MP to wage of 42.6 for highly educated workers and 24.1 for less educated workers. The lowest gap is found in the SOE sector.[25]

The excess of MP over wages for both highly and less-educated workers is in sharp contrast to that reported for urban workers in Fleisher and Wang (2001b), where wages of less-educated workers significantly exceed their marginal products for a sample of urban enterprises in the early 1990s. While this change for production workers is consistent with the hardening of budget constraints for SOEs in the mid- to late 1990s, the large excess of MP over wages is a puzzle. A possible explanation is monopsony power (Fleisher and Wang 2004), which causes the marginal cost of hiring workers to be higher than the wage and thus MP to be higher than the wage. Another possible reason is high quasi-fixed costs of labor such that workers receive large non-monetary benefits, but the observed gaps appear too large to be explained by non-monetary payments alone. Additionally, quasi-fixed labor costs, such as social insurance programs and non-wage compensations, are largely independent of hours worked. If such costs are very high, firms may adopt longer working hours via overtime to substitute for hiring more workers. Hence, it reduces the number of workers in the firm, and thus raises the marginal product per worker, although the marginal product per labor hour may not be as high.[26]

5. Education and Marginal product

If the gap in marginal product between two classes of labor can be entirely attributed to educational difference, the ratio of the marginal products of highly educated and less educated workers can be used to calculate a crude measure of the return to schooling in production. If we substitute sample mean values of the respective inputs and schooling differential in equation (4), we obtain

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[25] As shown in Table 3c, for non-SOE domestic firms, the average earnings of highly educated workers are lower than that of less educated workers, although their marginal products are not. One possible explanation might be that the firms include owners' income in the reported earnings. Since owners may have high income due to profit but less education, it results in higher average income of low educated workers. This case shows another problem of using earnings to evaluate the effect of education.

[26] For example, Li and Zax (2003) finds that non-SOE sectors have much longer working hours than the SOE sector.

$$\frac{\overline{MP_s}}{\overline{MP_p}} = (1+\bar{r})^{\overline{sw}} \quad (8)$$

We can evaluate (8) using the estimated parameters reported in Table 2 and the mean values of the relevant variables reported in Table 1. For the mean schooling differential between the two worker groups of 5.9 years, the implied mean return to schooling in production across the sample firms is 30.8%.

The simple calculation of the return to schooling in production based on equation (8) attributes all the productivity difference to education alone. To account for the influence of other observed and unobserved factors, we estimate a Mincer-type equation (7) with year- and firm- fixed effects in which dependent variable is the log ratio of the predicted marginal products for high- and low-educated workers, respectively, in each sample firm. The regressors are the firm-specific schooling difference between the respective worker classes and firm-specific experience gap defined as the difference in years of experience between the two classes of workers, as well as firm and time fixed effects. For the sample, Guangzhou and Shanghai have the largest education gap, with the education difference of 6.2 and 6.1 years, respectively. The foreign involved firms have the largest education gap, with 6.2 years of difference between two classes of workers; while SOE sector has the smallest gap, which is 5.5 years. This sorting of workers appears to be consistent with comparative advantage hypothesis proposed and tested by Gibbons *et al.* (2005). However, less educated workers have more job experience, as expected; and on average work 1.7 more years than highly educated workers. In the SOE sector, less educated workers have the longest job experience compared to the highly educated group, with the difference of 2.6 years; while the number for non-SOE domestic firms is only 1.0 year.

The estimation results are shown in Table 4. The estimated coefficient of schooling equals 0.168 and is significant at the 1% level, implying a rate of return equal to about 18.3%. When the experience terms are not included in the regression (specification 2), the coefficient of schooling is 0.219, which implies a rate of return of approximately 24.5%. As expected, the effect of schooling is larger without controlling for experience. In both regressions of Table 4, the estimated return to schooling is lower than the simple calculation based on equation (8), 30.8%. The estimated returns in production are larger than the estimates based on earnings as reported, for example, by Heckman and Li (2004) who estimate a return of about 11% using 2000 data. This is consistent with our observation that the return to education based on earnings underestimates the impact on production. The underestimation comes from the depression of the wage gap between highly educated and less educated workers relative to the gap of their MP, as discussed above. The estimated effect of experience is statistically insignificant in the linear term but significant at the 10% level at the quadratic term. However, the magnitude for the quadratic term is very small and not economically significant.

Table 4a shows the estimation results when equation (7) is estimated for each city and each ownership sector in the sample. For Shanghai and Guangzhou, the estimated return to education is positive and highly significant. For Tianjin and Chengdu, the effect of schooling is statistically insignificant; while for Beijing, it is negative. The highest estimated return to schooling is for Guangzhou, 141.1%. The second highest return is in Shanghai, 107.5%. Recall that both Shanghai and Guangzhou also exhibit very high estimated marginal products of labor. Schooling seems to contribute the most in production in Shanghai and Guangzhou, and these two cities are among the most developed cities with the highest degree of marketization in China. The result indicates that high effect of education on production is probably associated with the stage of economic transition and economic development, leading to a more efficient sorting of workers among firms and more efficient allocation of factors within firms. Moreover, advanced technology, which is more likely to be used in developed cities, is likely to increase the marginal product of educated relative to less-educated workers (Gibbons, *et al.*, 2005), leading to an increase in return to schooling in production as it requires more education in order to operate it.[27]

[27] Given estimated effect of schooling for different models and sub-samples, the negative and significant coefficient estimated for Beijing is likely to be caused by type I error.

The estimation for each ownership sector tells a consistent story. The foreign-invested sector has the highest estimated coefficient of schooling, translating to a rate of return of 142.3%, and it is highly significant. In the SOE and Non-SOE domestic sectors, the estimated coefficient of schooling is statistically insignificant. This result, that the estimated return to schooling in production is highest in the foreign-involved sector, is consistent with our estimate of the highest returns for Shanghai and Guangzhou. Foreign-invested firms are most likely to operate efficiently and use the most advanced technology in their industries. SOEs operate in the least market oriented system. The statistically insignificant coefficient of the schooling variable for the non-SOE domestic firms is consistent with this explanation.

In most cases, the estimated coefficient of experience is statistically insignificant. For foreign involved firms, however, the effect of experience is positive and significant, with a 12.7% increase in marginal product per year of additional experience. The coefficient is negative and significant for Tianjin and non-SOE domestic firms. The varying (even contradicting) effects of experience on production may be due to inefficient training methods in these firms, so that experience does not generate increased human capital among workers.

6. Education and Total Factor Productivity

Finally we investigate the indirect effect of education by regressing TFP on firm's education measure. In Table 5, we report the result of various models in which total factor productivity (TFP) is the regress and average schooling of all workers is the regressor. It appears that the effect of education is statistically insignificant, but mostly positive, in all models estimated by either OLS or FE. Moreover, the magnitude of the coefficient is small as well. The estimation results remain insignificant when we include separate variables for average education of the two classes of workers, and also include the years of schooling of the CEO in the regression. The magnitude of the coefficient of

CEO's education is larger than that of average education.[28] The qualitative results remain unchanged when we separate ownership sectors.

We also estimate a regression in which TFP growth is the dependent variable, where TFP growth is defined as $\log(TFP_t)-\log(TFP_{t-1})$. The average annual growth rate for the overall sample is 11.3%, as reported in the last row of Table 5a. Clearly, foreign-involved firms have the highest annual TFP growth, at a rate of 14.7%; while the SOE sector has the lowest growth at 8.7%. Among cities, Guangzhou has the highest TFP growth with an annual rate of 16.6%, and Shanghai and Beijing follow it with a growth rate of 13-14% (not reported in the table). Chengdu has the slowest FTP growth with an annual rate of 3.3% on average.

Table 5a reports the results for various specifications of the regression. As we can see, the effect of education is mostly positive but almost always statistically insignificant. However, education has positive and statistically significant effect on TFP growth for non-SOE domestic firms. If the average education of all workers increases by 0.1 year, the TFP growth rate increases by 17.6%. A possible explanation of our insignificant estimates is the small change of average education within firms. For the sample, the average education increased only 0.02 year from 1998 to 99, and another 0.02 year from 1999 to 2000. Our attempt to capture the effect of education on TFP growth is probably also limited by the omission of the education of workers outside the firm in our regressions, and thus this source of external benefits is not reflected in our estimates

7. Conclusions

In this study, we investigate the role of human capital on production and estimate the effect of education using firm level panel data from China. We first estimate marginal product of workers in different education classes; we then evaluate the direct impact of schooling based on the difference of marginal product of the two classes of workers. We also assess the indirect effect of schooling on firms' total factor productivity. Our approach avoids problems that arise when wages do not accurately reflect worker

[28] Since we have only one year data on CEO's education, we cannot use fixed effects estimation.

productivity as is likely to be the case in China. It also reduces unobserved-ability bias and other biases due to firm-specific and both time invariant and time-varying factors. Our data allow us to stratify across regionally disparate cities and across ownership types. Thus we can assess the patterns of productivity differentials associated with the economic transition of China.

Our major findings are as follows. First, estimated marginal products are much higher than wages, and the gap is larger for highly educated workers. For the full sample, the average marginal product of highly educated is approximately 13 times larger than their wages. For less educated workers the gap is a little over half as large—still quite substantial. Second, it follows from the observation that the marginal product gap between highly educated workers and less educated workers is much higher than their wage gap that the return to education as measured by contribution to production is greater than when it is measured by earnings. For the overall sample, we find that the return to schooling in terms of marginal product ranges between 18.3-24.5%, much larger than the return based on individual earnings. Third, after controlling for the direct effect of education on marginal product, we are unable to identify an impact of workers' overall schooling level or of the firms' CEOs on firm TFP, although education does positively affect TFP growth in non-SOE domestic firms.

We find that human capital works differently across ownership sectors and regions. Advances of the market economy and technology are positively related to the effect of education on production. In the foreign-involved sector, the effect of education on marginal product is the highest, and it is also the largest for Shanghai and Guangzhou, the two most developed cities in China. The regional pattern of the impact of schooling on production is reflected in others ways. For example, the western city Chengdu has the lowest marginal products for all inputs and the lowest rate of TFP growth. Among ownership groups, the SOE category displays the lowest marginal products, and it also has the lowest rate of TFP growth, 8.7% per year, compared to 14.7% among foreign invested firms.

Our results show that the return to education is very high in the economically advanced areas of China. The evidence supports Heckman (2005), who states that China should increase investment in human capital. A further implication is that developed cities like Guangzhou and Shanghai will continue to attract relatively educated and talented workers, as will the foreign involved sector. As a consequence, regional inequality in China may get worse. Therefore, in order to reduce regional disparity without risking the costs of radical population redistribution, it may be beneficial to adopt policies that increase marginal products to attract human capital and physical capital into less developed areas.

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Table 1

Summary Statistics

Variables	**Unit**	**Mean**	**Std. Dev.**	**Min**	**Max**
Value-Added	1000 RMB	139258.7	912862.8	73	1.84E+07
Capital	1000 RMB	170627.8	488373.1	74	7043648
Employees					
Highly Educated Workers	Workers	203.05	331.68	5	4133
Less Educated Workers	Workers	676.52	926.48	7	10109
Average Schooling Years					
Highly Educated Workers	Years	16.72	1.12	16	22
Less Educated Workers	Years	10.82	1.44	6	12
Average Annual Earnings (Year 2000)					
Highly Educated Workers	1000 RMB	96.30	1362.11	0.09	27853.71
Less Educated Workers	1000 RMB	36.49	468.95	0.02	9600
Average Working Experience					
Highly Educated Workers	Years	12.71	6.52	0	31
Less Educated Workers	Years	14.39	7.42	0	31

Notes:

1. Data are for the 446 firms in five cities in China. Value added is sales less intermediate goods adjusted for final- and intermediate-goods inventory changes. Capital is the book value of total fixed assets. Workers with low education are defined to include occupations with average schooling less than 16 years, which mainly consists of basic and auxiliary production workers. Workers with high education are defined to include those occupations with average schooling 16 or more years, which consists of mainly engineering and technical personnel and managerial personnel (including sales). We exclude service personnel and other workers in the production function because they do not belong to any category related to production.
2. The maximum value of average earnings is unreasonably high, which should be caused by reporting errors. Since earnings are not used in our regression, the results will not be affected by those extreme values. Thus, we do not delete those observations.

Table 2

Fixed Effects Regression of Cobb-Douglas Production Function

Dependent Variable: Log(Value-Added)

	(1)	**(2)**	**(3)**	**(4)**
Log (Capital)	0.357***	0.347***	0.357***	0.344***
	(0.088)	(0.088)	(0.088)	(0.089)
Log (Labor with High Education)	0.535***	0.544***	0.487***	0.497***
	(0.154)	(0.154)	(0.156)	(0.157)
Log (Labor with Low Education)	0.346**	0.357**	0.368**	0.382**
	(0.151)	(0.151)	(0.152)	(0.153)
Constant	1.657*	1.656*	1.746*	1.746*
	(0.938)	(0.941)	(0.946)	(0.949)
Year Dummies	Yes	Yes	Yes	Yes
Interactive Dummies of Years and Sectors	No	Yes	No	Yes
Interactive Dummies of Years and Cities	No	No	Yes	Yes
Observations	1251	1251	1251	1251
Adjusted Overall R-Squared	0.49	0.49	0.49	0.49

Notes:
1) ***, **, and * represent significant level at the 1%, 5%, and 10% level, respectively.
2) The numbers in brackets are standard errors.

Table 2a

Robust IV Regression of Production Function (1998-2000)

Dependent Variable: Log (Value-Added)

Log(Capital)	0.289***
	(0.096)
Log(Labor with High Education)	0.444***
	(0.133)
Log(Labor with Low Education)	0.219**
	(0.136)
Constant	3.438*
	(0.456)
Observations	665

Instrumented: Labor with High Education, Labor with Low Education
Instruments: the number of applicants for high-education jobs, the number of applicants for low-education jobs, and the average number of days the two types of jobs are vacant.

Notes:
1) ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
2) The numbers in brackets are robust standard errors.

Table 3a

Marginal product (MP) of Inputs for All Sample Firms

Variables	Mean	Std. Dev.	Min	Max
MP of Capital	1.65	6.81	0.01	141.8245
MP of Highly Educated Workers	1017.97	2070.92	5.76	32407.7
MP of Less Educated Workers	210.25	629.73	1.04	11125.95
MP of Highly Educated Workers (Year 2000)	1239.15	2661.58	5.76	32407.7
MP of Less Educated Workers (Year 2000)	275.19	854.28	1.32	11125.95
Earnings of Highly Educated Workers (Year 2000)	96.30	1362.11	0.09	27853.71
Earnings of Less Educated Workers (Year 2000)	36.49	468.95	0.02	9600

Table 3b

MP of Inputs by City

	Beijing	Chengdu	Guangzhou	Shanghai	Tianjin
MP of Capital	2.04	0.85	1.79	2.22	1.31
MP of Highly Educated Workers	714.84	421.49	1358.95	1828.10	778.23
MP of Less Educated Workers	237.15	60.27	154.67	463.29	127.12
MP of Highly Educated Workers (Year 2000)	896.79	476.11	1592.16	2278.72	858.08
MP of Less Educated Workers (Year 2000)	332.90	66.24	212.56	597.02	137.27
Earnings of Highly Educated Workers (Year 2000)	342.13	32.66	35.91	32.91	20.86
Earnings of Less Educated Workers (Year 2000)	121.61	13.59	13.15	17.81	10.70

Table 3c

MP of Inputs by Ownership

	SOEs	Foreign Involved Firms	Non SOE Domestic Firms
MP of Capital	0.39	1.66	2.49
MP of Highly Educated Workers	301.61	1738.85	818.80
MP of Less Educated Workers	67.35	371.90	153.40
MP of Highly Educated Workers (Year 2000)	301.61	1738.85	818.80
MP of Less Educated Workers (Year 2000)	67.35	371.90	153.40
Earnings of Highly Educated Workers (Year 2000)	274.20	40.82	32.39
Earnings of Less Educated Workers (Year 2000)	100.13	15.44	54.28

Table 4

Fixed Effect Regression of Mincer-Type Equation

Dependent Variable: Log (MP_s/MP_p)

	(1)	**(2)**
Difference in Schooling Years	0.168***	0.219***
	(0.076)	(0.073)
Difference in Experience	-0.038	
	(0.028)	
Quadratic Difference in Experience	0.003*	
	(0.002)	
Constant	0.719*	0.598
	(0.433)	(0.431)
Observations	1297	1297
Number of firms	443	443
Adjusted R-squared	0.006	0.017

Notes:
1) ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
2) The numbers in brackets are standard errors.
3) Fixed effects and the coefficients for year dummies are not reported.

Table 4a

Fixed Effect Regression of Mincer-Type Equation for Each City and Ownership Sector

Dependent Variable: Ln (MP_s/MP_p)

	across Cities					across Ownership Types		
	Beijing	**Chengdu**	**Guangzhou**	**Shanghai**	**Tianjin**	**SOEs**	**Foreign Involved Firms**	**Non-SOE Domestic Firms**
Difference in	-0.237*	-0.089	0.880***	0.730***	0.275	0.037	0.885***	-0.022
Schooling Years	(0.129)	(0.179)	(0.321)	(0.243)	(0.232)	(0.122)	(0.164)	(0.131)
Difference in	0.047	-0.057	0.006	0.063	-0.21**	-0.076	0.127**	-0.22***
Experience	(0.047)	(0.064)	(0.131)	(0.073)	(0.099)	(0.087)	(0.050)	(0.054)
Quadratic Difference	0.003	-0.003	-0.010	-0.002	-0.004	0.0002	0.007	0.013***
in Experience	(0.003)	(0.009)	(0.011)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	2.940***	2.366**	-2.720	-2.333*	0.290	1.282*	-3.59***	1.479**
	(0.770)	(1.069)	(1.920)	(1.251)	(1.280)	(0.661)	(0.988)	(0.734)
Observations	293	338	248	260	158	358	453	489
Number of firms	100	116	85	89	53	120	155	169
Adjusted R-squared	0.007	0.0003	0.072	0.001	0.0002	0.003	0.012	0.0003

Notes:
1) ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
2) The numbers in brackets are standard errors.

Table 5

Regression of TFP on Schooling of Workers

Dependent Variable: TFP

	Whole Sample			Ownership Types		
				SOE	Foreign involved	Non-SOE domestic
	OLS	**FE**	**OLS**	**FE**	**FE**	**FE**
Average Education of All Workers	0.023 (0.019)	-0.019 (0.027)	0.025 (0.78)	0.042 (0.039)	0.009 (0.031)	-0.003 (0.039)
CEO Education			0.031 (1.36)			
Constant	1.108*** (0.239)	1.813*** (0.331)	2.31 (4.93)	1.397*** (0.479)	1.352*** (0.406)	1.745*** (0.483)
Observations	1293	1224	470	437	498	466
Adjusted R-squared	0.11	0.01	0.084	0.02	0.06	0.01

Notes:
1) Regressors are the average education of workers including high- and low-educated workers.
2) ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
3) The numbers in brackets are standard errors.

Table 5a Regression of TFP Growth on Schooling

Dependent Variable: TFP growth

	Whole Sample		Ownership Types		
			SOEs	Foreign Involved Firms	Non-SOE Domestic Firms
	OLS	**FE**	**FE**	**FE**	**FE**
Average Education of	-0.003	0.353	0.245	-1.082	1.757**
All Workers	(0.017)	(0.504)	(0.921)	(0.943)	(0.742)
CEO Education	0.012				
	(0.014)				
Constant	-0.137	-4.182	-2.889	13.079	-21.38**
	(0.303)	(6.172)	(11.550)	(11.318)	(9.088)
Observations	789	716	196	254	268
Adjusted R-squared	0.01	0.001	0.01	0.0001	0.002
Average Annual TFP Growth		11.3%	8.7%	14.7%	10.0%

Notes:
1) ***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
2) The numbers in brackets are standard errors.
3) TFP growth is defined as $\log(TFP_t)-\log(TFP_{t-1})$.