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Economic transition, higher education and worker productivity in China

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ABSTRACT

We investigate the role of education on worker productivity and firms' total factor productivity using a panel of firm-level data from China. We estimate the returns to education by calculating the marginal productivity of workers of different education levels based on estimates of the firm-level production function. We also estimate how the education level of workers and CEO contributes to firms' total factor productivity. Estimated marginal products are much higher than wages, and the gap is larger for highly educated workers. Our estimate shows that an additional year of schooling raises marginal product by 30.1%, and that CEO's education increases TFP for foreign-invested firms. Estimates vary substantially across ownership classes, the effect of schooling on productivity being highest in foreign-invested firms. We infer that market mechanisms contribute to a more efficient use of human capital within firms.

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) found that China's high and rising regional income inequality reflected 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 (2001, 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. The Chinese government, recognizing this imbalance, has sharply increased resources allocated to the development of new colleges and universities (Li, in press; Wang et al., 2009). Sound policy requires knowledge of how education affects production and productivity, especially in a country like China, where wages may not accurately reflect productivity because the allocation of labor resources is significantly affected by incompletely developed labor markets, and 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 (Li, 2003; Li and Luo, 2004; Wang et al., 2009; Yang, 2002; Zhang et al., 2005). However, we cannot infer that these changes in relative wages by education level closely reflect changes in relative marginal products associated with schooling, because there remain many labor-market distortions inherited from the system of central planning and rigid allocation of labor through the planning process. 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 have the interior and western regions. We address the question: as China's industry has transformed from a planned- to market allocation of resources, do the private returns to schooling as reflected in wage differentials

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accurately reflect differences in the true marginal product associated with education?

We present estimates of the effects of human capital in production using a panel of firm-level observations. This procedure allows us to compare wage rates with the marginal products of the workers receiving these wages. Our data permit us to exploit the advantages of both differencing between different groups of workers within a firm and fixed-effect (FE) estimation (differencing over time), helping to reduce or eliminate potential sources of bias due to time-invariant and even time-varying unobservables correlated with firm characteristics. We also adopt the procedure of Olley and Pakes (OP) (1996), extended by Levinsohn and Petrin (LP) (2003), in which we attempt to control for firm-specific time-varying productivity shocks in production function estimation. [1]

Finally, we compare estimated productivity and the impact of human capital on production across ownership types. 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 transformation of labor markets affecting the allocation of human capital.

We proceed as follows. First we specify a value-added production function in which labor is divided into highly educated and less educated workers. Next we derive the marginal products of the two types of workers from the estimated production function. Then we use information on average schooling 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 Section 5, we estimate the effect of education on marginal product and on total factor productivity, respectively. Section 6 concludes.

2. Methodology

We specify the following value-added production function

$$Y_{it} = A_i K_{it}^{\beta_k} L_{sit}^{\beta_s} L_{pit}^{\beta_p} e^{u_{it}} \tag{1}$$

where Y is output measured by value-added, K is capital, L_s is the number of highly educated workers, L_p is the number of workers with less education, and u is a disturbance term for firms $i=1, 2, \ldots, n$ and from year $t=1, 2, \ldots, T$. The parameters β_k, β_p, and β_s are the output elasticities of the corresponding inputs.[2]

This specification is based on 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 (2004) specifies the production function to include number of hours worked by skilled workers and unskilled workers in investigating the spillover effects of human capital in the United States using plant level data. In the production functions specified by Hellerstein et al. (1999), workers are distinguished by different demographic characteristics including education.

While we argue that it is appropriate to disaggregate labor by schooling level inside the production function, it is also possible that the educational level of workers may help to develop and adapt to new technology, and then to increase firm TFP. Thus we investigate both the direct effect of education on production and its indirect effect through TFP. 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.

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

$$MP_{s_{it}} = \hat{\beta}_s \frac{Y_{it}}{L_{s_{it}}} \text{ and } MP_{p_{it}} = \hat{\beta}_p \frac{Y_{it}}{L_{p_{it}}}. \tag{2}$$

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 to convert one worker with low education into a worker with high education. Then, under the assumption that the difference in marginal products between the two types of labor results only from the difference in education, we have

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

or

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

(The subscript t is suppressed here and forward.) Eq. (4) implicitly defines a rate of return to schooling in production in each firm.

There are two problems in obtaining unbiased estimates of the production elasticities in Eq. (1) and, from them, the rate of return based on Eq. (4). The first problem is unobserved firm-specific effects correlated with the regressors (Tybout, 2000). A related problem is that unobserved technology shocks that can bias estimates of the production elasticities in Eq. (1). The simplest method for dealing with unobserved firm-specific effects is to estimate the production function using a first-difference or firm-fixed-effects (FE) procedure. The FE procedure can also control for firm-specific productivity shocks that are constant over the time period covered by the panel. A problem with the FE approach is that it assumes unobserved firm-specific characteristics are fixed over time.

A preferred procedure would be to use the method of Olley and Pakes (OP) (1996), extended by Levinsohn and Petrin (LP) (2003). The OP/LP method uses intermediate-goods expenditure or investment expenditure as a proxy for time-varying firm-specific productivity shocks. The OP procedure requires information on investment as a proxy for unobserved firm-specific productivity shocks. Their basic assumption is that a firm's investment is a monotonic function of firm-specific productivity shocks, given its capital stock. However, since about 70% of our firms report no investment, we could not use the OP method. Instead LP uses material or intermediate goods as a

[1] Hellerstein et al. (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 approach.

[2] We use the Cobb–Douglas functional form for simplicity in exposition as is common in the literature. In our empirical implementation, we also estimate a translog specification and report the results in Section 4.

proxy. In this case, we don't face the problem of have "zero" observations as most firms use intermediate goods or material. Therefore, we apply the LP procedure in our production function estimation along with the FE procedure.

Following LP, we impose two assumptions: (1) the use of materials is a monotonic function of unobserved firm-specific productivity shocks and capital, and (2) unobserved firm-specific productivity shocks follow an AR(1) process. Based on these assumptions, we construct a moment condition to estimate coefficients of production function.[3]

An alternative method, which makes further demands on the data, is developed in the dynamic-panel estimation literature (Chamberlain, 1982, Anderson and Hsiao, 1982, Arellano and Bond, 1991, Arellano and Bover, 1995; Blundell and Bond, 1998, 2000). Most recently, Ackerberg et al. (2006) provide a method to generalize the fixed-effects approach in a dynamic framework. ACF criticize the approach of the OP and LP procedures in that coefficients of variable inputs such as labor are not identified in the first stage. In OP/LP, the essential assumption is that firm-specific productivity shocks are a scalar function of investment (in OP) or intermediate goods (in LP) and the given capital stock. With this assumption, OP/LP identify coefficients of variable inputs (labor) in the first stage and then identify a coefficient of capital. However, ACF argue that the OP/LP approach's identification of variable inputs in the first stage fails. To overcome this problem, ACF do not estimate labor coefficients in the first stage. Instead, ACF impose additional assumptions: (i) capital is determined in period $t-1$; (ii) labor is chosen between period $t-1$ and t, and the productivity shock is known in period t. With these assumptions, they calculate firm-specific productivity shocks assuming an AR(1) process and then estimate coefficients of labor and capital together. Assuming that labor is determined by firm-specific productivity and capital, they used the lagged value of labor to estimate labor coefficients. Unfortunately, ACF's lag structure results in the loss of a substantial proportion of our observations. Given our three-year panel data, we must drop 1/3 of the observations in order to implement ACF.

We report estimates of Eq. (1) and its variants using both a FE approach and the LP approach. We also have attempted the ACF approach and the results are not reasonable, probably because of the small usable sample.

The second problem is in the influence of unobserved ability and observed and unobserved factors other than education on worker marginal products. Observable firm-specific factors include such influences on relative marginal products, as firms' location, ownership type, and product characteristics. Such influences can also bias the estimated effect of education on marginal products. There is insufficient worker-specific information in our data for us to estimate the possible extent of ability bias and/or worker heterogeneity in our estimates of the return to providing workers with additional schooling (Heckman and Li, 2004). However, our framework for estimating the effect education presented below can also mitigate such a bias.

Assume that the average 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 caused by factors other than education. Then we transform Eq. (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

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

Eq. (6) can be expanded to include additional human-capital variables such as experience so that

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

where b is an estimate of r, and ex is the difference in average experience between highly educated and less educated workers.[4]

The left-hand side of Eq. (7) is the log-difference in marginal product between highly educated and less educated workers. An advantage of this specification is that it allows us to difference out time-invariant and even time-varying unobservables within a firm 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 type, etc. Those firm-specific characteristics may be time-varying or invariant, and some of them may be correlated with education level of workers.[5] Within a particular firm, Z_{it} is invariant across worker groups, and thus will be differenced out. Therefore, this empirical specification helps to mitigate the potential omitted variable problem. Additionally, in this framework is that firm-specific markups are also differenced out in estimating the effect of education. This is a common problem when measuring a firm's productivity based on the value of output rather than physical units of the output as it is difficult to distinguish true productivity from firm-specific markups. Moreover, this differencing also removes the effect of wage differentials caused by local living costs.

Eq. (7) is estimated using fixed-effects (FE) regression. In this setup, FE estimation can reduce or eliminate omitted ability bias. It is well known that omitted ability bias is a big problem in estimating the effect of schooling on individual earnings because of the possible correlation between unobserved ability and schooling level. In our Eq. (7), omitted ability bias may also be present for the same reason, because marginal product may be affected by unobserved ability that is correlated with education. In the Mincer earnings equation, the omitted ability bias problem cannot be resolved with panel data using FE estimation, 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. Thus, in FE estimation, firm-specific ability will be differenced out, assuming that the average ability difference between highly educated and less educated workers stays constant over time.[6] Therefore the combination of the log-difference specification plus the panel nature of our data allows us to avoid many potential sources of bias due to time-varying and -invariant omitted variables.[7]

The approach discussed above combines fixed-effects estimation and within-firm productivity comparison. It relies on the observed

[3] The LP method can be implemented by using Stata command (Petrin et al., 2004).

[4] Strictly, the rate of return is $r = e^b - 1$.

[5] For example, some firm-level unobservables may affect marginal productivity and the firm's education requirement on hiring, and thus are correlated with education level of the workers.

[6] The ability bias will still be present if the ability difference between highly and less educated workers varies across years. This will depend on whether the marginal skilled and unskilled workers hired and dismissed as firms adjust their labor force over time have higher or lower ability than the average workers of that quality.

[7] In our case, we first difference out time-varying and invariant unobservables by differencing the marginal products between two classes of workers and then difference out the time-invariant unobservables from the time mean in the fixed-effects estimation.

Table 1
Summary statistics.

Variables	Unit	1998		1999		2000	
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Value-added	1000 RMB	106,784.300	771,063.900	165,940.800	1,194,563.000	154,414.400	764,583.500
Capital	1000 RMB	145,331.300	341,521.600	175,225.900	502,279.100	197,417.800	597,091.900
Employees							
Highly educated workers	Workers	213.221	316.398	200.021	324.698	209.474	370.374
Less educated workers	Workers	702.698	969.714	670.518	929.093	673.686	924.386
Average schooling years							
Highly educated workers	Years	16.646	1.083	16.703	1.111	16.722	1.123
Less educated workers	Years	10.832	1.436	10.799	1.441	10.844	1.436
Average annual earnings							
Highly educated workers	1000 RMB					26.032	54.286
Less educated workers	1000 RMB					12.628	13.866
Average working experience							
Highly educated workers	Years	11.758	5.907	12.171	6.270	12.937	6.249
Less educated workers	Years	13.575	6.957	13.881	7.215	14.630	7.240

Data are for the 425 firms in five cities in China. For some variables, the number of observations is slightly smaller due to missing values. 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 activities such as health care, food service, and other "service" not directly related to production. Wage data are only available for 2000.

changes in the schooling composition of the workers in firms in our sample to identify the estimated productivity effects of schooling. As shown in Table 1, both the average numbers of highly and less educated workers changed by about 5% per year between 1998 and 2000. For example, from 1998 to 2000, the average number of highly educated workers changed from 213 to 200, and then to 209; and average number of less educated workers changed from 703 to 670, and then to 674. The schooling gap between highly and less educated workers also varied across those years, although by a smaller magnitude.

A related identification question is whether the year-to-year adjustment of the educational composition of a firm's workforce is exogenous or the result of a firm's response to changing technological factors inside the firm. Clearly, work force changes that result from mandated retirement are exogenous. Moreover, quits in response to changes in workers' circumstances or outside offers can be considered exogenous. In contrast, workforce changes that are due to layoffs and new hires are more likely to be responses to changing productivity conditions inside the firm as well as to market conditions. However, many layoffs in China were largely in response to mandates received from government ministries attempting to reduce perceived over-employment and thus have a significant exogenous component. For example, layoffs exceed 7 million workers in 1998 and 1999 and 5 million in 2000 (China Labor Statistical Yearbook, 2002, 2005). In addition, labor adjustments that respond to changes in product demand, relative wages or productivity shocks from outside a firm should also be treated as exogenous. But skill adjustments in response to technological changes within a firm (e.g. upgrading technologies, introducing new products, etc.) should be considered endogenous in the context of this study. For example, newly adopted technology may be more complementary to skilled than unskilled workers.

We hope that the impact of endogeneity of education difference is small and that the FE estimation that takes care of time-invariant omitted variables will also mitigate this endogeneity problem. The ultimate solution for this issue is to find good instruments for education differentials between worker groups. We tried to identify some possible instruments in the data to run Instrumental Variable (IV) estimation of the production function. The results are reported and discussed in Section 4.

The next step is to estimate the indirect effect of education, i.e., the effect of education on total factor productivity (TFP).[8] 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). Education can facilitate the development and adaptation of new technology (Benhabib and Spiegel, 1994), the spillovers 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, 2004). At the micro-level, however, little is known about the indirect effect of education within a firm on its TFP after its direct effect on production has been controlled for. We investigate this issue by regressing firm TFP on the firm's education measures, including average schooling of all workers and the years of schooling of the CEO.

3. Data and variables

Our data are derived from a firm-level survey, the Productivity and Investment Climate Survey (PICS) conducted by China's National Bureau of Statistics for the World Bank. The sample covers 998 manufacturing firms selected in five cities and five manufacturing industries. The survey obtained retrospective data for 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 targeted size categories. The resulting 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's degree or above. As a result, there remain 425 enterprises in our sample.[9]

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.

[8] 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.

[9] While we cannot claim that the sample or our results are representative of all of China, our empirical results are noteworthy and suggest important areas of further research.

Table 2
Estimation of production function.

Dependent variable: log (value-added)	(1)	(2)	(3)	(4)	(5)
Log (capital)	0.358*** (0.091)	0.347*** (0.091)	0.354*** (0.091)	0.342*** (0.092)	0.344*** (0.003)
Log (labor with high education)	0.538*** (0.160)	0.556*** (0.161)	0.477*** (0.162)	0.498*** (0.163)	0.422 (0.157)
Log (labor with low education)	0.344** (0.159)	0.346** (0.159)	0.381** (0.160)	0.386** (0.161)	0.202 (0.156)
Constant	1.639* (0.988)	1.652* (0.990)	1.725* (0.993)	1.734* (0.995)	
Year dummies	Yes	Yes	Yes	Yes	Yes
Interactive dummies of years and sectors	No	Yes	No	Yes	Yes
Interactive dummies of years and cities	No	No	Yes	Yes	Yes
Observations	1176	1176	1176	1176	740
Adjusted overall R-squared	0.488	0.487	0.496	0.494	

***, **, and * represent significant level at the 1%, 5%, and 10% level, respectively.
The numbers in brackets are robust standard errors.
Columns (1) through (4) are estimated using standard FE estimation, with a dummy variable for each firm; column (5) uses the method by Levinsohn and Petrin method (2003).

Value-added is defined as sales less intermediate goods and adjusted for final- and intermediate-goods inventory changes.[10] 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). In the survey, each firm is asked to provide information on the average education level for its full time employees across different occupations.[11] We average the workers' schooling codes for each occupation and designate each occupation level as either highly educated or less educated based on the average schooling of workers in the occupation. 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] Our survey data provides information on schooling and experience by occupation level for 2000 and employment for the years 1998 and 2000. We impute employment data for 1999 using the average employment of 1998 and 2000.[13]

In our sample, each firm has on average 207 highly educated workers averaging 16.7 schooling years and 681 less educated workers averaging 10.8 schooling years.[14] Thus, for the average firm, approximately 23% of the workers are in the highly educated category. This proportion is above the average for China. For example, in the year 2002, the proportion of workers in China with at least a college degree (including three-year college) was about 15.8% in urban areas (China Labor Statistical Yearbook, 2005). However, our data include major cities, in which the education level should be higher than all urban areas, which include small and middle-sized cities. Another reason for the relatively high proportion of highly educated workers is that we exclude those workers who contribute negligibly to production (see footnote 12).

The survey also contains information on the total labor cost (compensation) for each occupational group, but the information 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 divided by the number of workers in the group. The estimated annual earnings include wages, bonus, subsidies and other items. As shown in Table 1, the average annual earnings for the workers with high and less education are 26,032, and 12,628 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 less 6 years. The cross-year sample average experience for highly educated and less educated workers is 12.31 and 14.05 years, respectively. We group the firms into three ownership categories: state-owned enterprises (SOE), foreign-invested enterprises (Foreign-Involved Enterprises, FIE), and non-SOE domestic enterprises.

4. Marginal product of highly educated and less educated workers

Table 2 presents estimates for the production function specified in Eq. (1) based on two-way fixed effects using both firm- and year-dummy variables to control for firm- and year-specific fixed effects and based on the LP method for structural identification of the production function. We tested the Cobb–Douglas (C–D) estimates against the more general translog specification and were unable to reject C–D. The F-value for this test is 1.41 and the p-value is 0.21. Therefore, we report only the C–D estimation results. Column 1 shows estimation results for the basic specification, and columns, 2, 3, and 4 show results including interaction terms between year dummies and city dummies and/or ownership sector dummies in order to capture omitted time-varying but city or sector specific factors the omission of which could lead to biased estimation results. Column 5 reports the estimation results based on the LP method of structural identification.

The results are very robust across specifications, including the LP procedure. 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 0.20–0.39; while the elasticity of highly educated workers

[10] It is unusual to have information on inventory changes in Chinese data, and we cannot be sure of our data's accuracy in this regard. However, since it represents measurement errors in the dependent variable, the impact should be small as long as the measurement errors are random.

[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's degree and 1 is doctor's 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 school. 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 those worker categories which we identify as engaged in activities such as health care, food service, and other "service" not directly related to production, because we believe that such workers would not be employed by conventional cost-minimizing firms and that they contribute negligibly to production of measured output.

[13] We assume that the education requirement for each occupation is constant for all three years.

[14] The average year of schooling is calculated using average education of each occupational group weighted by the share of workers in that group.

[15] We test for constant returns to scale, and the null hypothesis of constant returns to scale is rejected.

is much larger, in the range of 0.42–0.56. The finding of higher elasticity of highly educated workers relative to less educated workers is consistent with other studies, for example, Pavcnik (2002), and Moretti (2004).

In the estimation discussed above, we have controlled for firm-specific omitted variables and for time-varying but sector- or city-specific factors via FE and LP estimation. Yet, it is still possible that input adjustments within a firm are endogenous, especially for labor adjustments because of the relative flexibility in adjusting labor in a short time period. Often, this problem is ignored in the literature due to the difficulty of finding instruments.[16] In order to test for the influence of this possible endogeneity, we adopt an instrumental variable (IV) estimation procedure. To be successful, we must identify variables that may be correlated with firms' labor adjustment but not to firm-specific heterogeneity. Such variables can come from supply-side influenced by local labor-market conditions.[17] There are four such potential variables in our data: 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 average number of weeks to fill the last the low-education job.[18] We believe that these variables are mostly out of the control of a particular firm, and represent exogenous influences, and are correlated with a firm's labor adjustment.[19] Given the possibility of reporting errors, we run IV regression using a robust method which down-weights sample outliers to make the estimation less sensitive to measurement errors.

Table 2a shows the results of IV estimation of Eq. (1). The results of the first stage regression suggest that we are using reasonably "strong" instruments. We also partially test the validity of the instruments by the over-identifying restriction test of Davidson and MacKinnon (1993) and do not reject the null that the over-identifying instruments are valid assuming of a subset of the instruments is valid and identifies the model. The IV results are generally consistent with those in Table 2. We use the LP estimates column (5) of Table 2 in our subsequent analysis.

The marginal products (MP) calculated from the LP estimates of column (5) in Table 2 are shown in Table 3. 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 51%. It varies widely across location and ownership type. SOEs show the lowest return to capital investment with a rate of 15%, while non-SOE domestic firms show the highest return of 83%. 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.

The estimated MP for capital in Shanghai is 76%, the highest among all of the cities in our sample; while the lowest is that for Chengdu at 29%. If capital investment under the market mechanism goes to the area that provides the highest MP, the less-developed western region will not be attractive for investors. As a result, regional inequality is probably aggravated as China moves to a more market-oriented economy. This result is consistent with the finding in Fleisher et al. (2010) based on provincial level data. An important policy of the Chinese government to address growing regional inequality is its "Go-West" program, which emphasizes capital investment in western areas.[20] Clearly, to implement the Go-West program, it is important to raise the MP of capital through improving infrastructure and fostering technology transfer to lagging regions. This is a topic worth further investigation (Démurger et al., 2002, Démurger, 2001).

Table 2a
IV estimation of production function.

Dependent variable: log (value-added)	
Log (capital)	0.280*** (0.096)
Log (labor with high education)	0.434*** (0.139)
Log (labor with low education)	0.291** (0.145)
Year dummies	Yes
City dummies	Yes
Ownership sector dummies	Yes
Constant	3.152*** (0.506)
Observations	593

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

In Table 3 we see that the marginal product of highly educated workers exceeds that of less educated workers by a large margin. Among ownership groups, the foreign-invested sector has the highest MP of both classes of workers, while the SOE group has the lowest. The ratio of MP of highly educated workers in FIEs to that in SOEs is 4.95, and the ratio is 9.5 for less educated workers. The relatively low MP of workers for SOEs probably reflects the over-staffing in this sector persisting from the old command economy. In almost all cases, workers are paid less than their marginal products. In Table 3, on average, the year 2000 wage of highly educated workers is about 7.5% of their MP; and the wage of less educated workers is about 19.2% of their MP. Across ownership groups, the FIE sector has the highest gap, and the SOE sector has the lowest for both types of workers.[21]

As discussed in the Introduction, given the transitional nature of the Chinese economic system from the traditional command economy and rigid labor allocation, the gap between value of marginal product and wages is not unexpected. An excess of MP over wages in Chinese enterprises has been noted in a large number of studies, including Fleisher and Wang (2004) who cite a significant body of earlier research on both urban and rural collective enterprises. Those studies refer to employer monopsony power as one possible explanation. Parker (1999) reports evidence of employer monopsony in the state-owned machine-building industry. Monopsony power is an appealing explanation of an

[16] In a recent study, Pavcnik (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] These variables have been reported for one year only. Based on the phrase of the question in the survey, it is unclear which year those instrument variables are referred to. We 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] It is possible that these instrumental variables are still related to firms' recruiting efforts. Unfortunately, based on data availability, these are the best instruments we can use. It is our hope that the corruption of our supply-side instruments by demand influences is weak due to the presence of frequently supply-side restrictions in China. On the other hand, we view our IV estimation as an additional robustness check on our LP and FE estimates.

[20] 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 as a crucial plan for reducing regional gap.

[21] A referee suggests that our approach may neglect capital-skill complementarity and the use of more sophisticated capital of highly educated workers. By neglecting this relationship, we may have overestimated higher-schooled workers' marginal product. We cannot observe the capital used by different workers within a firm, and even if we had data on worker assignments to particular items of physical capital, identifying the output uniquely associated with these relationships would be extremely difficult. One albeit imperfect approach to this issue, however, is to test for complementary between highly educated workers and capital in general through estimation of a translog production function. The result shows that the cross-partial derivative of highly educated workers with capital is negative but insignificant at any reasonable level, while the marginal product for less educated workers is about the same in both specifications of the production function. Thus, the less-restrictive translog functional form does not provide evidence of a lower MP-wage gap for highly educated workers. We believe, without more detailed data on capital, functional form alone may not be able to control for the complementarity between capital and different types of workers.

Table 3
Marginal product (MP) of inputs.

Variables	All	SOEs	Foreign involved firms	Non-SOE domestic firms
MP of capital	0.512	0.153	0.450	0.825
MP of highly educated workers	272.531	94.879	470.120	219.628
MP of less educated workers	48.508	17.062	90.701	32.568
MP of highly educated workers (year 2000)	350.728	99.564	625.095	252.971
MP of less educated workers (year 2000)	65.508	12.992	122.859	45.096
Earnings of highly educated workers (year 2000)	26.032	15.670	39.937	19.756
Earnings of less educated workers (year 2000)	12.628	11.209	15.904	10.449

Table 4
Fixed-effect estimation of the Mincer-type equation.

Dependent variable: log (MP_s/MP_p)				
	All	SOEs	Foreign involved firms	Non-SOE domestic firms
Difference in schooling years	0.263*** (0.078)	0.084 (0.109)	0.910*** (0.174)	0.066 (0.159)
Difference in experience	−0.001 (0.035)	−0.027 (0.079)	0.153*** (0.052)	−0.229*** (0.072)
Quadratic difference in experience	0.004* (0.002)	0.002 (0.005)	0.008* (0.004)	0.008* (0.005)
Constant	0.510 (0.444)	1.363** (0.592)	−3.469*** (1.059)	1.018 (0.900)
Year dummies	Yes	Yes	Yes	Yes
Observations	1161	321	390	441
Number of firms	424	112	142	159
Adjusted overall R-squared	0.011	0.0002	0.015	0.002

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

excess of MP over wages in China, because of a number of market imperfections and distortions, including obstacles to labor mobility. Those distortions may also prevent the labor market from achieving an approximation of a competitive equilibrium. Moreover, financial intermediation is underdeveloped, leading to capital constraints that limit firms' expansion to optimal size. Documented and anecdotal evidence implies that borrowing, land-use, and electricity (power) constraints preclude many enterprises from achieving their profit-maximizing size, and there may also be unobserved risk premia required for investment in additional capital. All of these constraints are likely to be higher for non-SOE enterprises, and the existence of larger MP-wage gaps in the non-SOE sector is consistent with the constraint-plus-monopsony explanation.

5. Education, marginal product, and total factor productivity

In order to investigate the effect of education on worker marginal products, we estimate the Mincer-type Eq. (7) with year- and firm-fixed effects. The regressors are the firm-specific schooling difference between the respective worker classes and firm-specific experience gap. The education gap varies across cities and ownership sectors. For the sample, Guangzhou has the largest education gap of 6.21 years, while Beijing has the smallest with the gap of 5.64 years. FIEs have 6.23 years of difference between the two classes of workers; while SOE sector has only 5.5 years. However, less educated workers have more job experience, and on average have worked 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 2.78 years; while the difference for non-SOE domestic firms is only 0.93 year.

The estimation results are shown in Table 4. The estimated coefficient of schooling equals 0.263 for the whole sample and is highly significant, implying a rate of return to education in production equal to about 30.1%. Since our estimate has controlled for omitted ability bias, we compare it with the estimates based on earnings data using IV estimation. There is a very short list of studies on returns to education based on earnings or wages that control for ability bias using Chinese data. Li and Luo (2004) estimate a rate of return of 15.0% using 1995 data in urban by generalized method of moments (GMM) estimation. Heckman and Li (2004) estimate a rate of return of 14% by IV estimation using data from 2000. Wang et al. (2009) estimate a marginal return of about 15% for 2002. Clearly, our estimated effect of education based on marginal productivity is much larger than the estimates based on earnings reported in the literature.[22] This result is not surprising given that the wages are much lower than the marginal revenue product for workers in China, as discussed above.

The higher estimated return to education based on marginal product compared to that based on earnings is also consistent with the comparison of wage ratios to marginal product ratios between the two skill groups. For year 2000, the overall ratio of MP between highly and less educated workers is 5.3, while the ratio between their wages is only 2.1. The largest wage compression was found in the SOE sector, where the ratio of MP between two types of workers is 7.7 but their corresponding wage ratio is merely 1.4. The smallest compression is in the FIE sector with the ratio between MP and wages 5.1 and 2.5, respectively. It appears that the largest wage compression between highly educated- and less educated workers is found in the SOE sector. For example, in the SOE sector, highly educated workers were paid about 39% of their counterparts in the foreign-invested sector, while less educated workers were paid 70% of the corresponding group in foreign-invested firms. In contrast, the MP ratios for highly and less educated workers between the two sectors are more nearly equal—16% and 11%, respectively.

The estimation results for each ownership sector are also reported in Table 4. The foreign-invested sector has the highest estimated coefficient of schooling (0.91, implying a rate of return of 148%), and the estimate is highly significant. In the SOE and non-SOE domestic sectors, the estimated coefficient of schooling is much smaller with a rate of return in the range of 7–9%, and it is statistically insignificant.

[22] The estimates of return to education using earnings data by the Ordinary Least Squares (OLS) estimation suffer from the omitted ability bias (Card, 1999). Most studies using IV estimation find an estimated return higher than that using the OLS estimation because of the attenuation bias caused by measurement errors (Butcher and Case, 1994, and Ashenfelter and Zimmerman, 1997).

Table 5
The effect of schooling on TFP.

Dependent variable: TFP				
	All	SOE	Foreign involved	Non-SOE domestic
Average education of all workers	0.028 (0.190)	0.050 (0.044)	0.032 (0.027)	0.009 (0.033)
CEO education	0.036* (0.016)	−0.017 (0.028)	0.084*** (0.028)	0.014 (0.021)
Constant	2.023*** (0.321)	2.476*** (0.614)	1.447** (0.594)	2.727*** (0.452)
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes
Observations	1162	322	395	442
Adjusted *R*-squared	0.144	0.16	0.19	0.06

Regressors are the average education of workers including high- and low-educated workers.
***, **, and * represent significant level at 1%, 5%, and 10%, respectively.
Standard errors are in parenthesis.

The lower return to education in production for the SOE sector reported here is consistent with the findings based on earnings data in China.[23] We infer that the relatively large impact of education on production in foreign-invested enterprises reflects a more advanced stage of economic transition and economic development and a concomitantly 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 the foreign-invested sector, is likely to increase the marginal product of educated relative to less educated workers (Gibbons et al., 2005); or in other words, education equipped them with the capacity to use more advanced capital, both leading to a higher return to schooling in production.

For the overall sample, the estimated effect of experience is statistically insignificant in the linear term but significant at the 10% level at the quadratic term. Among sectors, the estimated coefficient of experience for SOEs is statistically insignificant, but negative for non-SOE domestic firms. The varying (even contradicting) results for SOEs and non-SOE domestic firms are consistent with the specific pattern for those firms during the course of economic transformation in China. These enterprises are still not fully transformed to the market mechanism in terms of their ownership structure, objectives, and management. Foreign involved firms, however, show a pattern comparable to firms in a market economy, and the effect of experience as measured by marginal product and the rate of return derived from it is positive and significant, although smaller than that for education. It is plausible that the difference in the effect of experience between foreign firms and others is due to inefficient on-the-job training in non-foreign firms.

Finally, we investigate the indirect effect of education by regressing TFP on firms' education measures, including average schooling of all workers and the years of schooling of the CEO. For the three-year period, on average, TFP grew by 10.58%. FIEs had the fastest TFP growth of 13.9%, while SOEs had the lowest growth of 7.3%. In Table 5, we report the result of the TFP regressions. The estimated effect of average worker education is statistically insignificant on TFP. [24] This is not surprising given that the effect of education of workers has been controlled for in the production function.[25] However, the coefficient of CEO's education is positive and statistically significant at the 10% level. It shows that if CEO's education increases by one year, TFP is expected to increase 3.6%.

The TFP regression across ownership sectors tells a similar story to that for worker marginal products based on the Mincer regressions. As can be seen in Table 5, for SOE and non-SOE domestic firms neither average education of workers nor CEO education has a significant effect on TFP. However, in the FIE sector, although average education of workers does not have a significant effect on TFP, CEO's education does have a quite strong effect. If CEO's education increases by one year, TFP increases by 8.4%.

6. Conclusions

We have investigated the role of human capital in production using firm-level panel data from China. We first estimate the marginal product of workers in different education classes and then estimate the direct impact of difference in schooling on the difference in marginal products between 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 are used as a measure of marginal product, as is likely to be the case in China, and it also reduces unobserved-ability bias and other biases due to firm-specific and both time-invariant and time-varying unobserved factors. We also apply recent developments in production function estimation techniques developed in the work of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006) to control for time-variant firm-specific productivity shocks. Additionally, by stratifying across ownership types we assess the causes 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. Second, the marginal product difference between highly educated workers and less educated workers is much higher than their wage difference, and the return to education as measured by contribution to production is greater than that is measured by earnings. For the overall sample, we find that the return to schooling in terms of marginal product is about 30.1%, while the return in terms of wages reported in a large body of research on China is much lower. Third, after controlling for the direct effect of education on marginal product, we are unable to find a significant impact of workers' overall schooling level on firm TFP, yet the education of the firms' CEOs has a positive and significant effect on firm TFP. This latter effect applies only to the foreign-invested sector.

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, we find that the effect of education on worker marginal product is the highest, as is the effect of CEO's education on TFP. Among ownership groups, the SOE category displays the lowest marginal products, and it also has the lowest rate of TFP growth, about one half of that among foreign-invested firms.

Our results show that the return to education in production is much higher in the more market-oriented sector. One implication is

[23] In Li (2003), the estimated return to college in the private sector is about 29% higher than that in the SOE sector.
[24] Since we have only one year data on CEO's education, we cannot use fixed-effects estimation. We assume it is the same for all three years to run a pooled regression.
[25] The estimation results remain similar when we include separate variables for average education of the two classes of workers.

that foreign involved sectors and developed cities like Shanghai will continue to attract relatively educated and talented workers, exacerbating. As a cosequence, regional inequality in China. Therefore, in order to reduce regional disparity, it should be beneficial to adopt policies that increase marginal products to attract human capital and physical capital into less-developed areas. Continued economic reforms to speed the transition of state-owned and collectively owned domestic enterprises into market-oriented firms should help China move in this direction.

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