# Understanding China's workforce competitiveness: a macro analysis

Yue Qu and Fang Cai
*Institute of Population and Labor Economics, Chinese Academy of Social Sciences, Beijing, China*

## Abstract

**Purpose** – The purpose of this paper is to examine the relationship between training and education and associated workforce productivity and competitiveness also, to identify new effective strategies for China to maintain and enhance workforce productivity given the depleting abundant workforce supply.

**Design/methodology/approach** – Based on data from China's manufacturing firms that included all state-owned and non-state-owned enterprises with annual revenue greater than ¥5 million in 2004, the authors calculate marginal labor productivity through production function and derived the relationship between workers' education and associated productivity.

**Findings** – At the time China arrives at a Lewisian Turing Point, workforce quality can substitute the quantity to maintain its competitive advantage. Higher workforce productivity generated from improved human capital can offset increases in labor cost, thus creating new impetus for sustained economic growth.

**Research limitations/implications** – Formal education and workplace learning are complementary in maintaining and enhancing a productivity workforce. To build a new competitive edge for China's economic growth in the short run, enterprise-based training should be a requirement in all industries.

**Practical implications** – The authors offer implications for HR managers and organizations on talent management strategies. Implications for governments to develop policies that promote and foster workplace learning and skill building activities are also presented.

**Originality/value** – This study is one of the first adopting large-scale enterprise productivity data to show China's workforce competitiveness by examining the relationship between workforce productivity and training and education.

**Keywords** China, Manufacturing industries, Competitive strategy, Education and training

**Paper type** Research paper

Since economic reform and open-door policy in the early 1980s, China's economy has sustained a momentum of high growth rate. For decades, China as a developing country has been under a dual economy with unlimited supply of rural surplus labor (Lewis, 1954, 1972). This unique advantage made it necessary and possible for China to achieve global competitiveness and economic growth by taking advantage of large quantity of workforce supply at low labor cost. However, with increased urbanization and industrialization, rural surplus workforce has gradually depleted due to continued large-scale migration to urban areas. This phenomenon has been reflected in the recent labor shortage phenomenon (yong gong huang) across the country (Cai, 2010).

Apparently, China's economy is at a Lewisian turning point (LTP) Cai, 2008), where the advantages of the quantity of workforce weakens while wages and associated cost of labor increase. In other words, before reaching the LTP, the supply of China's workforce was literally unlimited, and industrial sectors in urban areas were able to obtain any amount of workforce they needed to produce goods and services that fueled

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the economic growth. Reaching and beyond the LTP, the advantage of the quantity of the labor force is to be weakened. Therefore, it is necessary for China to explore new competitive advantages in the increasingly globalized environment. The key competitiveness of an economy is in its workforce that is engaged in the economic growth-related activities (Judy and D'Amico, 1997). This study is to offer a macro analysis and facilitate the understanding that the ultimate competitive advantage of China is in its workforce in the intense globalization process.

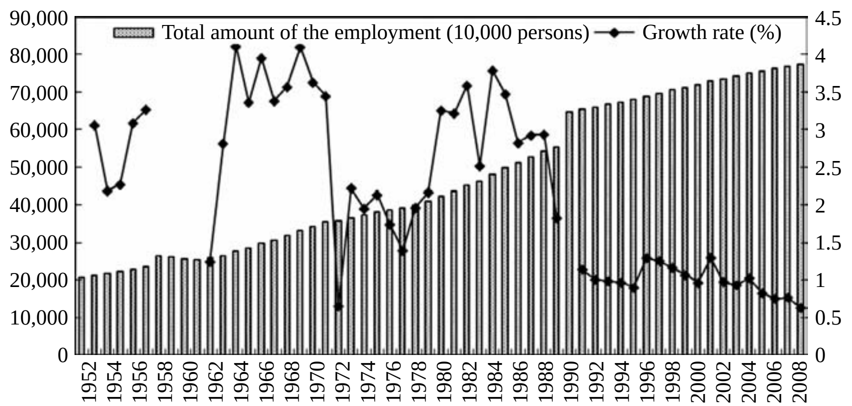
## Purpose and significance

Given the research problem presented above, the purpose of this study aims to address the following research question:

*RQ1*. What is the ultimate competitive advantage of China's workforce?

In exploring this question, we examine the relationship between workforce training and education and associated productivity from organizational perspective in the manufacturing industry. We further analyze the effect of dependent factor of enterprises' workforce productivity based on workforce productivity function, especially the effect of training and education variables on workforce productivity and related contributions.

The significant of this study can be seen from the following analysis. First, at a macro level, the growth rate of China's overall employment has been decreasing. Figure 1 shows changes in China's employment situation since 1950s. While total number of employment has been steadily increasing, the growth rate shows a clear tendency of slowing down. The trend is especially clear after the turn of the century, where the rates of growth in employment for all years are under or close to 1 percent. In particular, 2008 recorded the slowest employment growth since reform and opening-up, at an annual rate of 0.64 percent. While such slow growth rates in recent years may be partially attributed to the impact of international financial crisis, it is evident that even before the crisis, China's employment growth has already been lingering at a very low level, with a growth rate below 0.8 percent for both 2006-2007 (Figure 1).



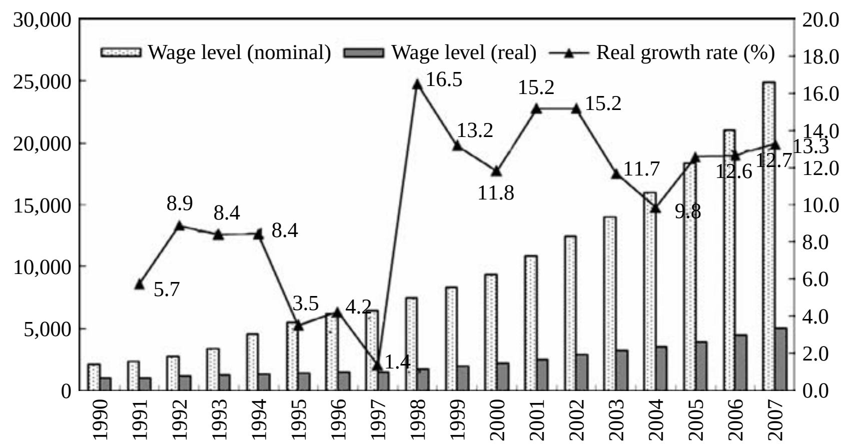

**Source:** *China Statistical Yearbook*, China National Bureau of Statistics (CNBS)

**Figure 1.**
Total employment and employment growth rate

In general, the growth of an economic entity relies on factor input in the earlier stage of industrialization, but depend more on technology advancement after the initial stage (Lin and Sun, 2003). Such shift is often accompanied by industrial structure upgrading and productivity enhancement (Cai *et al.*, 2003). Featured with economic dualism, China's resource endowment is fundamentally different before and after the arrival of LTP. Before the LTP, the supply of workforce was abundant, where it accommodated China's resource attributes for developing labor-intensive industries or adopting an industrial structure that focused more on labor intensity and less capital intensity. This was a major reason that explained why China's advantageous labor-intensive industries leapt forward after entering WTO. When surplus labor in the rural areas migrated to urban non-agricultural sectors, manufacturing industries obtained comparative advantage, relying on the abundant and low-cost workforce, thus contributed significantly to China's economic growth (Zhao, 2005). However, given current trend in population aging and low birth rate, the shortage in workforce and the rise of labor cost are inevitable (Flaherty *et al.*, 2007). Clearly, with diminishing workforce supply, China can no longer rely solely on the quantity of workforce to maintain competitive advantages in the global market, but to seek new sources to sustain its long-term growth.

Second, the cost of labor has been increasing in recent years. Economic theory predicts that the price of labor will increase when the supply is no long abundant or unlimited. As shown by Figure 2, since the mid-1990s, especially after the new century, average wage in China has witnessed a substantial increase, over 10 percent, for both nominal and real growth rates. It is important to note that wage increases almost coincide with the slowing down of employment growth in 1990s, especially after 2000, as shown by Figure 1. Combining Figures 1 and 2, it is not difficult to see that with rapid wage growth, slightly lagging behind the growth of employment rate, there is a clear pattern that the changes in labor cost in China are associated with the changes in the quantity of workforce supply.

After the LTP, changes of workforce supply and associate cost may entail prolonged and profound implications for the economy (Cai, 2008). First, changes of workforce supply may force a region or a country to transform its labor-intensive industries




**Source:** *China Statistical Yearbook*, *China Labour Statistical Yearbook*, NBS

**Figure 2.**
Wage level and growth rate

to capital or technology intensive. Second, upsurge in wage may change relative prices of capital and labor, pushing enterprises to use more capital to replace labor and minimize total cost. Such adjustments require corresponding improvement in human capital as represented by workforce knowledge and skills. In the meantime, workforce productivity will have to escalate to offset the rise in labor cost and support China's competitive advantage, providing new sources for long-term growth. Therefore, more research is required to examine changes of workforce's quality and productivity, as well as their impact on China's long-term economic development.

Third, while the growth of workforce supply has been slowing down and the cost of labor increases rapidly, China's workforce productivity continued to show significant improvement. China is far ahead of other countries in terms of manufacturing productivity growth. The average productivity's growth rate in China is not only higher than the developed countries but also higher than other developing countries (Van Ark, 2008). This implies that a strong labor productivity growth may partially offset the impact of labor cost increase, and constitute a new competitive source for the Chinese economy.

In short, with decreased rate of employment growth and increased labor cost, China faces a challenge to maintain sustained productivity in its future economic development. This study further examines the relationship between productivity and the quality of human resources in China's manufacturing industry to highlight its competitive advantage in the long run.

**Literature review**

Human capital at organizational level is composed of a number of components, including health care, migration, and training and development (Becker, 1993). Among them, education, experience, and knowledge, and skill have been considered the most important components that determine workforce productivity and labor compensation (Becker, 1993; Li and Ding, 2003). Existing studies have examined the rates of return on human capital extensively (Mincer, 1974; Lai, 1998; Li and Ding, 2003; Li and Li, 1994; Psacharopoulos, 1994; Sturm, 1993; Wang *et al.*, 2007). For these studies, findings vary in different countries at different economic development stages and different time periods under different socioeconomic contexts. For example, Psacharopoulos (1994) reported that average return to education was 10.1 percent worldwide and 9.6 percent in Asia. As China's labor market gradually took shape along with the economic reform, the rate of return on training and education showed a trend of gradual growth (Li and Ding, 2003). In urban areas, return on training and education was found to be 3.8 percent in 1988 (Li and Li, 1994), 5.74 percent in 1995 (Lai, 1998), 7.63 percent in 1999 (Li and Ding, 2003), and 8.45 percent in 2002 (Wang *et al.*, 2007). However, previous studies on return on education were mostly focused on measuring the impact of education on income with census data. Such analyses are based on the following two assumptions as shown by Figure 3:

(1) education creates a pulling effect on productivity; and

(2) the increase of average income is the outcome of productivity improvement.

In other words, existing studies have been following a traditional path to analyze indirect relationship between education and productivity at a household level, instead of enterprise level (Lai, 1998; Li and Ding, 2003; Li and Li, 1994; Mincer, 1974; Wang *et al.*, 2007). While research along this line is insightful, the analysis based on household survey data is unlikely to capture accurate information on the characteristics of enterprises where human resources are engaged in. Thus, it is insufficient to understand the status and the trend of workforce productivity.

A major reason for these studies was caused by available data sources. It may be relatively easy to obtain productivity related data at organizational level, but it has been difficult to obtain data combining productivity and education of workforce at the organizational level. Such data are essential to understand the real return on education. The inherent shortage of data sources made it difficult to estimate the return on training and education for workforce productivity, other than justifying the well-accepted theory of human capital on return on education in terms of income from individual perspective.

This study adopted a different data source and examined the relationship between workforce productivity and training and development from organizational, and industry perspectives. Through the analysis, we aim to address the research question about China's workforce competitiveness.

## Method

*Analytical framework*

We specify the following production function to investigate the relationship between employees' productivity and their levels of training and education:

$$Y = AJ^{\alpha}L_1^{\beta_1}L_2^{\beta_2}L_3^{\beta_3}L_4^{\beta_4} \tag{1}$$

where Y is output at enterprise level, A is the level of technology. K is physical capital. $L_1$, $L_2$, $L_3$, and $L_4$ represent employees with education from junior high school or under ($L_1$), senior high school ($L_2$), college ($L_3$), and graduate school ($L_4$), respectively. We consider $L_i$ different types of input factor and their productivity can be estimated and differentiated. For individuals, higher human capital as represented by training and education may create more output in productive activities, and thus they are supposed to generate higher economic outcomes.

In equation (1), employees' productivity can be further specified as:

$$MPL_i = \frac{\partial Y}{\partial L_i} = \frac{\beta_i Y}{L_i} \quad (\mathrm{i} = 1,\ 2,\ 3,\ 4) \tag{2}$$

Combing equations (1) and (2), without considering differences in workforce quantity, the differences in marginal labor productivity (MPL) of workers with different training and educational background in the same organization can be represented by the elasticity of labor, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$. By estimating the production function, we can then derive the relative labor productivity with respect to different types of workforce at the organization level.

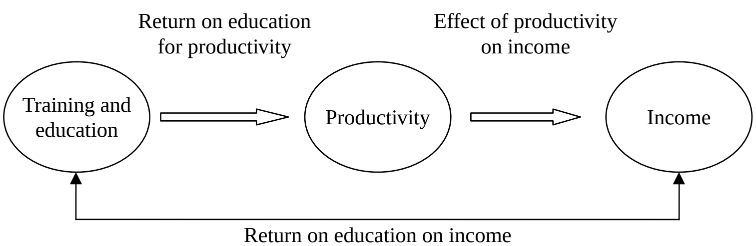



**Figure 3.**
Indirect measurement: relationship of education, productivity and income

Furthermore, to analyze productivity in relation to training and education at industry level, we can use aggregate data from organization level based on equations (3) and (4) in a similar way. For example, to obtain return on education and MPL level for industry, we can estimate production function of equation (3) for selected industry and aggregate the calculation based on equation (4). We can further derive the relationship between employees' average education level and labor productivity of each industry. By using the g-fields decomposing method (Fields, 2003), we also determine the contribution of education and training to labor productivity based on the estimated result of production function equation (3):

$$Y = AK^{\alpha}L^{\beta} \tag{3}$$

$$MPL = \frac{\partial Y}{\partial L} = \frac{\beta Y}{L} \tag{4}$$

*Data*

Data for this study were from an organization-level national survey of manufacturing firms conducted by China's National Bureau of Statistics (NBS) in 2004. The original data included 300,000 industrial organizations in 31 provinces, major cities, and autonomy regions. For this study, we selected 30 manufacturing industries based on the two-digit industrial codes defined by NBS. The subset of the data included a total of 259,412 manufacturing organizations with annual sales revenue greater than 5 million RMB in 2004. These organizations included both state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). The data contained variables of organizational production characteristics and attributes of the employees, such as salaries and training and education background. Table I reported descriptive statistics of the samples included in this study.

In addition to the above data source, we also collected national and industrial data on training and education published in the *Statistical Yearbooks* by NBS from 2002 to 2008. The purpose was to compare the results of the study with national and industry reality.

## Result

We first examined relative productivity at an aggregate level for all employees in the data. We defined the group of lowest education, junior high school or below, as a reference group. In other words, we normalized this group's relative productivity

| Variable | Mean |
|---|---|
| Sales (¥1,000) | 62,587.58 |
| Value added (¥1,000) | 20,053.86 |
| Fixed capital *per capita* (¥1,000) | 84.47 |
| Years of education | 10.61 |
| Junior high school and below (%) | 57.07 |
| Senior high school (%) | 31.03 |
| College/university (%) | 34.48 |
| Graduate (%) | 0.30 |

**Source:** Calculation based on the NBS data of selected manufacturing enterprise that include all SOEs and NSOEs with annual revenue greater than RMB 5 million in 2004

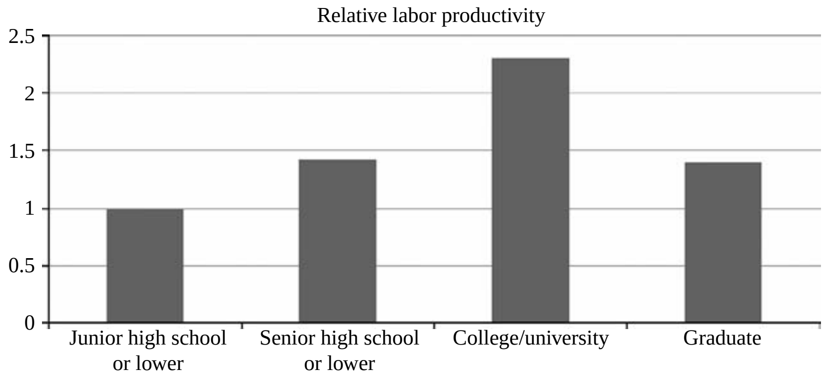
**Table I.** Descriptive statistics

as 1 to derive productivity of other groups as shown in Figure 4, i.e. $\beta_2$, $\beta_3$, $\beta_4$, relative to $\beta_1$. It was clear that productivity of employees with higher education was higher than those with lower education. For example, productivity of employees with senior high school was 1.4 times of those with junior high school education. The productivity of those with college degrees was 2.3 times of those from junior high school. However, employees with graduate school education or above showed a lower productivity than those with college degrees. A possible explanation for this result was that for manufacturing organizations, employees with master's degree or higher might not directly influence production process. A second potential reason could be that management or R&D-related activities could not be effectively captured by the production function specified.

Next, we examined the relationship between education and human resource productivity at organizational level. Through estimating function (3) for the 30 industries included in the data, we derived labor productivity of each industry based on function (4). Figure 5 shown positive relationships between average years of education and capital intensity of the manufacturing organizations, and between educational level and their productivity. Specifically, percentage of employees with different education level was calculated through education variables. In order to maintain continuous nature for the education variables, average years of education was estimated based on the percentage of employees with different education level and weighted average of respective years of education[1].

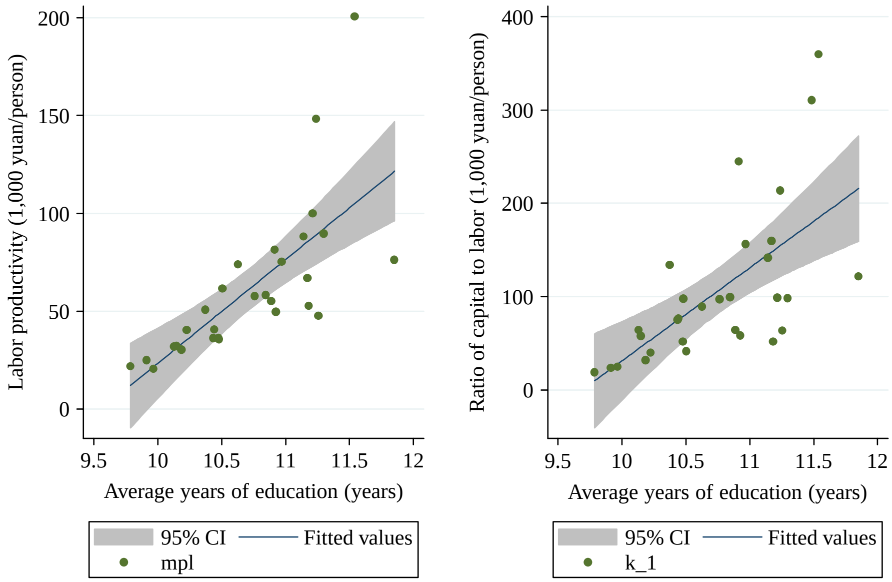
The positive relationship between educational level and employee productivity indicated that while workforce supply became limited, the improvement of labor productivity and economic growth was supported by higher labor quality (Figure 5(a)). Meanwhile, the positive relationship between education and capital intensity shown in Figure 5(b) showed that China's industrial upgrading was actually coupled with employees' higher level of education. In other words, industries with higher capital-labor ratio tended to require employees to have higher education level.

To determine the contributions of training and education to workforce productivity, we further estimated the effect of dependent factor of the enterprises' workforce productivity based on productivity function equation (3) for the samples. Our focus was




**Source:** Calculation based on the NBS data of selected manufacturing enterprise that include all SOEs and NSOEs with annual revenue greater than RMB 5 million in 2004

**Figure 4.**
Relative labor productivity: different types of workforce




**(a)** **(b)**

**Source:** Calculation based on the NBS data of selected manufacturing enterprises that include all SOEs and NSOEs with annual revenue greater than RMB 5 million in 2004

**Figure 5.**
Education level and the labor productivity/the capital intensity

on the effect of education variables on workforce productivity, including both the coefficients and the contribution. We conducted a regression analysis with workforce productivity as independent variable. We used three types of variables as dependent variables representing education level of employees and attributes of market, and enterprises. As for dependent variables about education, we used average years of education and proportions of enterprise employees at each education levels as two measures controlling for the following variables: the variables describing the attributes of enterprises including capital-labor intensity, sales (logarithm of sales revenue), and number of enterprises in the industry, as well as the variables describing external market environment represented by dummies of the industry and the region.

Table II reported the results of regression analysis. In model 1, we used average years of education as a measurement for education. In general, workforce productivity increased by 17 percent as a result of one more year of education. The stage-wise effects of education showed that labor productivity of an enterprise increased 23 percent (0.23) if an organization's employees were to be upgraded from junior high school level to senior high school. Similarly, labor productivity could be increased by an additional 100 percent (1.24-0.23) if the employees' education could be raised from senior high school to college graduates. Clearly, the biggest pulling effects on workforce productivity occurred at the stage of changing from high school to college graduates. Yet, currently, manufacturing workforce was primarily composed of those with junior or senior high education (Cai *et al.*, 2009). Therefore, developing training and education played a significant role in boosting workforce productivity.

**Table II.**
Regression analysis: contributions of education to productivity

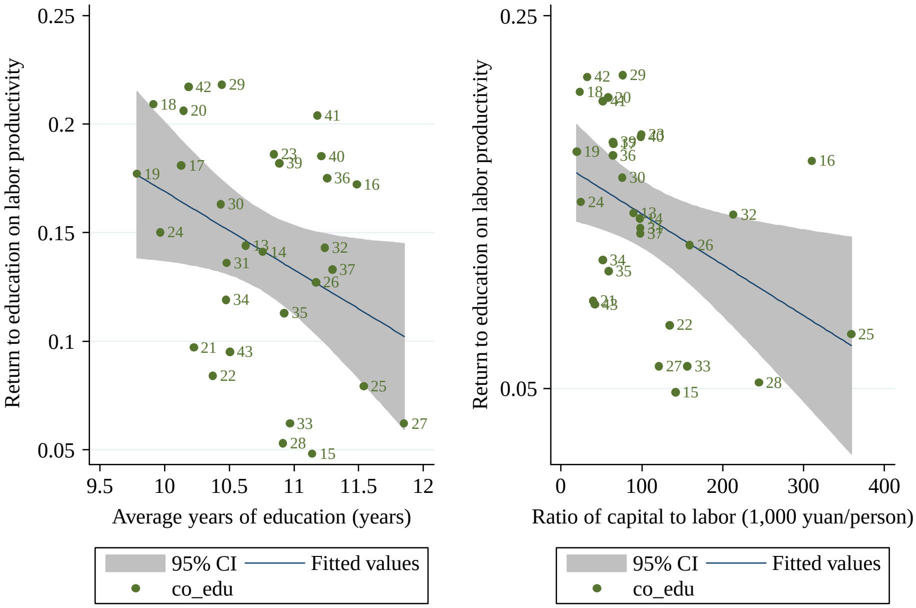
| | | | Model 2. Education level | | |
|---|---|---|---|---|---|
| Model 1. Average years of education | | | Junior high school-senior high school | Senior high school-college or university | College or university-graduate school |
| Coefficient | 0.17 | | 0.23 | 1.24 | 1.92 |
| Contribution | 0.05 | 0.06 | | | |
| $R^2$ | 0.23 | 0.24 | | | |
| The contribution of education/$R^2$ | 0.22 | 0.24 | | | |

**Note:** Employees with education of junior high school or under served as reference group in model 2
**Source:** Calculation based on the data of the manufacturing enterprise that include all SOEs and NSOEs with annual revenue greater than RMB 5 million in 2004

Furthermore, based on the above results, we decomposed the contribution of each dependent factor in the model for workforce productivity according to the g-fields decomposition method (Fields, 2003). The results showed all the explanatory variables in the model explain 23-24 percent of the workforce productivity. Education contributed 5.13-5.66 percent to overall workforce productivity, and 20-25 percent of the total contribution of all the explanatory variables in the model. Both the coefficient and the contribution of the education variables suggested that the education level of employees has created significant impact on workforce productivity of the enterprises under study.

To understand the difference of the return on training and education among different industries, we further examined the rates of return on education in relation to workforce productivity in different manufacturing sectors. It is well accepted that the improvement of overall human capital in organizations raises workforce productivity (de la Fuente, 2011). When labor force becomes a limited and scarce resource, economic development would be accompanied by industrial upgrading, and thus organizations would require employees to obtain higher level of human capital (Cai, 2008). Generally speaking, labor-intensive industries require relatively lower level of human capital, while capital-intensive or technology- intensive industries requiring higher level of human capital (Cai *et al.*, 2003). In other words, industries with different capital-labor ratio tend to employ workers with different educational level. This provided a base for us to analyze the relationship regarding training and education, labor productivity, and capital intensity. Based on equation (3), we estimated rate of return for the 30 selected manufacturing industries to identify which industries have a higher rate of return on education. The results were shown in Figure 6.

Figure 6 shown the relationships between productivity return on training and education and between capital intensity and employee's educational level of selected industries, respectively. It demonstrated that returns on education were higher in industries with higher labor intensity, implying education has generated greater productivity in these industries. For industries that were more labor intensive, such as textiles (17), dressing and dyeing of furs (19), crafts (42), and rubber products (29), the average education level of workforce was relatively low, and the rates of return on education were relatively higher. In contrast, the return rate was as high as 21 percent in crafts (42), apparel (18) and rubber products (29), and 18 percent in textiles and fur products. On the other hand, in capital-intensive industries such as Coke,




**Notes:** Code of the industries: 13 agriculture food products; 14 food products; 15 beverages; 16 tobacco products; 17 textiles; 18 wearing apparel; 19 dressing and dyeing of furs; 20 lumber; 21 furniture; 22 paper and paper products; 23 publishing, printing and reproduction of recorded media; 24 entertainment products; 25 coke, refined petroleum products and nuclear fuel; 26 chemicals and chemical products; 27 medical products; 28 fibre products; 29 rubber products; 30 plastics products; 31 other non-metallic mineral products; 32 basic metals; 33 non-ferrous metals; 34 fabricated metal products; 35 general machinery and equipment n.e.c; 36 special machinery and equipment n.e.c; 37 transport equipment; 39 electrical machinery and apparatus n.e.c.; 40 office, accounting and computing machinery; 41 medical, precision and optical instruments, watches and clocks; 42 crafts; 43 recycling
**Source:** Calculation based on the data of the manufacturing enterprise that include all SOEs and NSOEs with annual revenue greater than RMB 5 million in 2004

**Figure 6.**
Return rate to education for different industries

refined petroleum products (25) and medical products (27) where education levels of workforce were high, the rates of return on education was relatively lower. These results implied that the improvement of training and education in labor-intensive industries may be more effective in improving overall productivity of manufacturing industry.

Lastly, we analyzed the above results in conjunction with available national statistics on training and education. As shown in Table III, the average education level of workforce in manufacturing industries have, in fact, been consistently higher than that of national average by more than 1 percent for the past seven years from 2002 to 2008. In particular, a majority of the national workforce, 75 percent, only had education from primary and junior high schools, with only 12 percent being senior high graduates in 2008, For the same year, those with colleges degrees was less than 7 percent, and around 5 percent was illiterate. Accordingly, the national average education for the entire workforce was 8.46 years. Furthermore, from 2002 to 2008, overall education level improved slightly, with average years of education up from 8.14 to 8.46, an improvement of only about three months. Meanwhile, education structure was slightly changed.

Table III.
Education level of employed population in China (2002-2008)

| | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|
| *National total* | | | | | | | |
| Illiteracy | 7.80 | 7.10 | 6.20 | 7.76 | 6.74 | 5.98 | 5.35 |
| Primary school | 30.00 | 28.71 | 27.40 | 29.22 | 29.95 | 28.32 | 27.67 |
| Junior high school | 43.20 | 43.74 | 45.00 | 44.11 | 44.85 | 46.86 | 47.76 |
| Senior high school | 13.10 | 13.62 | 13.00 | 12.14 | 11.85 | 12.19 | 12.47 |
| Three-year college | 4.30 | 4.82 | 5.00 | 4.46 | 4.25 | 4.32 | 4.29 |
| University | 1.60 | 1.91 | 2.00 | 2.14 | 2.14 | 2.13 | 2.25 |
| Graduate | 0.10 | 0.09 | 0.10 | 0.18 | 0.23 | 0.20 | 0.21 |
| Average years of education | 8.14 | 8.29 | 8.29 | 8.18 | 8.24 | 8.36 | 8.46 |
| *Manufacturing industries* | | | | | | | |
| Illiteracy | 1.30 | 1.47 | 1.20 | 1.65 | 1.35 | 1.16 | 1.13 |
| Primary school | 14.40 | 15.08 | 14.00 | 16.33 | 15.12 | 14.18 | 13.83 |
| Junior high school | 53.40 | 53.82 | 54.90 | 55.83 | 54.95 | 56.44 | 56.02 |
| Senior high school | 24.70 | 23.23 | 22.90 | 19.80 | 20.96 | 21.00 | 21.26 |
| Three-year college | 4.70 | 4.70 | 4.80 | 4.49 | 5.22 | 5.10 | 5.40 |
| University | 1.50 | 1.65 | 1.80 | 1.75 | 2.25 | 1.98 | 2.18 |
| Graduate | 0.10 | 0.05 | 0.10 | 0.14 | 0.16 | 0.14 | 0.19 |
| Average years of education | 9.55 | 9.47 | 9.51 | 9.32 | 9.49 | 9.51 | 9.56 |

**Source:** *China Labour Statistical Yearbook*, NBS

For example, the percentage of illiterate workforce was reduced from 7.8 to 5.35, the percentage of junior high graduates climbed from 43 to 48, and the percentage of bachelor degree holders hikes from 1.6 to 2.25 percent.

Although overall Chinese employees' training and education has been improving over the years, the pace of such improvement was relatively slow. For example, overall average years of education for national workforce increased only by 0.32 year (or less than four months) from 2002 to 2008 (the upper panel in Table III). On the other hand, in manufacturing industries, the workforce education levels had been relatively steady with insignificant improvement as indicated in the lower panel of Table III.

## Discussion

At the time China arrives at the LTP, the advantage of low-cost labor is gradually diminishing. By examining manufacturing industries, this study found that the competitive advantage of China's economic growth must be shifted to focusing more on workforce quality through training and education to improve productivity and support sustained economic growth. The results of this study also showed that enhancing employees' training and education in the manufacturing industries, particularly in high labor-intensive sectors, might play a remarkable role on improving workforce productivity.

The results of this study are consistent with other recent studies. For example, one study on China's workforce productivity also found that although wage and labor compensation rise rapidly, with declining labor intensity in China's manufacturing industry and the improvement of productivity, the Unit Cost of Labor Advantage (UCLA, labor compensation/labor productivity) had dropped in recent years. UCLA1 derived from MPL dropped from 44 percent in 2000 to 23 percent in 2007, and UCLA2 calculated with average labor productivity decreased from 27 percent in 2000 to 12 percent in 2007 (Cai *et al.*, 2009). Apparently, China's manufacturing industry can only maintain its competitive advantage if productivity growth can outweigh the growth of labor cost.

The comparison of manufacturing sector to the national average data indicated at least two important aspects. First, manufacturing industries have been able to attract higher quality workforce among all other industries to maintain their competitiveness in the global market from 2002 to 2008. Second, all other industries in China are facing similar challenges in improving workforce quality and competitiveness as faced by the manufacturing industries for productivity improvement.

While limited improvement in education in China may not be an indication of unsuccessful efforts in educational system development, it does offer important insight. At least, Table III has evidenced an important issue about developing high-quality workforce through formal education. That is, the outcome of education cannot be capitalized in short term. Instead, it requires an extended period of time to show tangible results in productivity improvement. Additionally, given the targeting population of general education being age groups from 5 to 16, the short-term impact of education in productivity will be further limited. On the other hand, the entire workforce is distributed across a much wider range of age groups. Accordingly, incremental improvement in educated population has a slower and lagging effect on the changes of overall workforce productivity.

Given the direct associations of workforce education with productivity in manufacturing industries found in this study and the extrapolations to the overall industry sectors, it is not difficulty to see that short- to mid-term workforce productivity improvement in China should heavily rely on enterprise-based training and development activities. Recently, the national outlines of mid- and long-term talent development plans: 2010-2020, has highlighted strategic goals for national talent development (Xinhua News, 2010). However, specific approaches have yet to be investigated, particularly in scholarly research. To this end, this study leads to the following implications for training policies at national and organizational levels.

To address the issue of improving workforce quality and productivity for global competitiveness, policies at organizational levels should be focused on offering alternative approaches other than formal education. Thus, it is critical to promote workplace learning and on-the-job training to enhance knowledge and skills of existing workforce. Compared to formal education, organization-based short-term on-the-job training has the following advantages. First, training content can reflect most recent development in knowledge and technology, and the skill requirements of respective functions and job roles. Second, on-the-job training can be flexible in delivery platforms and learning duration based on specific organizational needs. Third, workplace provide perfect settings for identifying learning needs, and learning transfer related outcomes can be assessed and measured subsequently (Wang and Spitzer, 2005). Therefore, to enhance organization-based learning, enterprises need to develop ways and to foster a learning culture focusing on on-the-job training for productivity improvement. The key is to build a workforce that is not only competent in improving productivity on existing job roles, but also competitive in embracing future challenges.

This study also offers important implications for HR managers and practitioners at organization level. Given the changing landscape of ongoing and anticipated future shortage in human resources (yong gong huan) that are required by the industries, HR managers need to proactively prepare for the changes and explore different HR practices in retaining, motivating and developing existing employees. New HR strategies should also be developed for attracting and recruiting future employees. This will allow organizations to maintain and improve their workforce productivity and competitiveness.

At national and provincial levels, government may consider formulating specific workforce training and development policies to encourage organizations to invest in training and development for their existing employees. To this end, a policy of "play or pay" may be considered. This system may be designed under the following structure. Enterprises either provide organization-based skill development training programs to employees, or contribute a proportion of their payrolls toward a regional or national pool of training and development fund so that a designated government agency may offer equivalent support and coordinate for organization-based skill development training programs.

This study also pointed to a future research direction. Given the importance of the contributions by training and education on workforce productivity, this study did not find graduate level training and education being associated with a higher productivity. It is necessary for future research to further explore and explain why the group of workforce with the highest education in the samples generated lower productivity than those with college degrees. Research in this area is critical for future research on workforce productivity and may provide important policy and practical implications for China's workforce competitiveness in the globalized market.

## Conclusion

While the past advantage of labor abundance is apparently close to an end with ongoing overall economic restructuring and adjustment, China must consider new workforce policy to promote productivity enhancement and offset the impact of labor cost increase. This study, through analyzing national data in the manufacturing industries, demonstrated that enhancing the quality of workforce through organizational-based training and development activities is likely to create new impetus for workforce productivity improvement and build new competitive edge for China's economic growth. The increased production complexity and intense global competitions require China's workforce to acquire expanded knowledge base and new competitive skills which cannot be supplied by existing educational system and cannot be accomplished by traditional workforce.

Under these circumstances, the quantity of workforce can be substituted by improved workforce quality in the forms of workplace learning and skill-based training activities in order to maintain China's workforce competitiveness. We conclude that higher labor productivity resulting from the improvement of human capital investment can offset the increase in labor cost and the reductions in workforce growth, thus providing a powerful engine to propel future economic growth. We further derive policy implications for government, organizations, and HR managers to promote and foster a learning culture for developing skill-based training and development activities. Future research on further investigating the group of workforce at graduate level is needed to understand its contribution to China's workforce productivity.

## Note

1. Average years of education – percentage of junior middle school graduates * 9 + percentage of junior middle school graduates * 12 + percentage of college graduates * 14 + percentage of university graduates * 16 + percentage of masters and above * 20.

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## Further reading

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## About the authors

Yue Qu is an Assistant Professor at the Institute of Population and Labor Economics (IPLE), Chinese Academy of Social Sciences. Her research interest is labor economics and industrial economics. She has been an Economic Consultant in World Bank in 2008, and a Visiting Scholar in International Food Policy Research Institute in 2011. She has published many papers in domestic and international academic journals. Yue Qu is the corresponding author and can be contacted at: quyue@cass.org.cn

Fang Cai is currently Director of the IPLE, Director of Human Resources Research Center, Chinese Academy of Social Sciences. Mr Fang Cai was awarded several national level awards, such as the Zhang Peigang Development Economics Prize and Soft Science Prize. He serves as Vice President of China Population Association, Vice Chairman of China Committee of International Human Dimensions Programme on Global Environmental Change, Member of Advisory Committee of the National Plan of China, and some ministries and local governments. He serves as Member of Editorial Boards for academic journals such as *Social Sciences in China*, *Economic Studies*. Mr Fang Cai's research focuses on theories and policies of agricultural economics, labor economics, population economics, China's economic reform, economic growth, distribution of income, and poverty, etc.