The Changing Demand for Human Capital at China's New Stage of Development

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Introduction

The Chinese labor market has witnessed a great transition in recent years, as evidenced by frequent labor shortage and rising wages for unskilled workers (Cai, 2007). In 2011, average monthly earnings for migrant workers grew 15% in real term compared to previous year (NBS, 2012). These changes have benefited workers but present new challenges for producers as labor costs rise. The particularly rapid rise in labor costs in manufacturing is evident in the fast growth in unit labor costs , the ratio between labor cost and average labor productivity. (Du and Qu, 2012). The difference in unit labor costs between China and developed countries is still substantial but the gap isclosing. Since 2004 US unit labor costs in manufacturing have averaged 0.6 while in China they have risen from 0.19 to 0.22.

It is expected that rising labor costs reflecting rising labor scarcity of labor may induce firms to adopt labor-saving technology, particularly in labor-intensive sectors where capital substitutes for labor. At the aggregate level, this change is known as industrial upgrading which also induces changing demand for labor.

With this shift toward more capital and technology inputs employers demand higher-quality labor rather than quantity of employees. In this case, it is good to know what features are associated with high quality of labor at the firm level.

Associated with industrial upgrading a number of questions arise. One is about the features of firms which seek higher quality labor. Another question at the new stage of economic development as China moves toward being a high- income economy, what types of workers are needed to facilitate industrial upgrading? Given the labor scarcity already revealed through rising market wages, are the firms responsive to the price and output changes when making hiring and firing decision? And if the firms' demand shifts to more-skilled workers will shifting demand casue an employment shock even China is short of unskilled labor? Taking advantage of the firm survey data, we try to answer these three questions.

Our data source is a nationally representative survey of 1644 manufacturing firms in China conducted by the Research Department of the People's Bank of China (PBC) in the fall of 2009. The authors contributed an employment module that included questions on employment changes and the implementation of the new Labor Law. The surveys were conducted in 25 cities located in eight provinces, including 4 coastal provinces (Shandong, Jiangsu, Zhejiang, and Guangdong), one northeast province (Jilin), one central province (Hubei), one northwest province (Shaanxi), and one southwest province (Sichuan). The sampling frame for the PBC national firm survey includes all firms who have ever had credit relationship with any financial institution, which is likely to under-sample very small firms. The average firm employs 499 production workers. See the appendix for summary of sample statistics.

The rest of the paper is organized as follows. The next section gives a brief introduction to the background of China's industrial transformation and changing demand for human capital. In the third section, taking advantage of firm survey data, we describe the firms with high demand for skills. The fourth section constructs an empirical model of labor demand function to analyze the firms' response to price and output changes. Some econometric concerns are discussed here. The fifth section presents our main empirical results and conclusions follow in the final section.

Industrial upgrading and the demand for human capital

As China's labor abundance declines with the aging of the population it is expected that industrial upgrading will cause a major restructuring of the economy and improvement in product quality, higher-quality services and increased value added production. The industrial upgrading will be evident in measures of improved total factor productivity (TFP) – measures of how efficiently inputs are used – rather than the traiditonal growth in the stocks of labor and capital. As the process of upgrading takes hold, there will be a shift from labor-intensive sectors to capital- and technology- intensive sectors. The industrial structure will shift from the heavy emphasis on manufacturing to services. Since the target of economic upgrading is to improve TFP and labor productivity, more emphasis can be expected on the quality rather than quantity of human capital.

With economic upgrading, the manufacturing sector can be expected to move up the value chain. . Already this process is underway in coastal areas where firms must respond to the increasing prices of production factors. In future, the process will extend to central and western China. Right now, although China has become the world factory, the ratio of value added to gross output in manufacturing is relatively low, about 0.26, compared to ratios of 0.49, 0.48, and 0.37 in the United States, Japan, and Germany, respectively. Several factors determine the role of manufacturing in the value chain, including the types of technology, management, and the level of skills, all of which are ultimately correlated with the level of human capital.

In addition to improved production efficiency, the economic upgrading also involves R & D, new product creation, and marketing, all features that rely on associated services for production. New industries will require intensive inputs of information, technology, management, and skills all of which will increase demand more sophisticated human capital in the forms of skills and creativity.

China has already witnessed a significant shift of the economy from primary to secondary industry in the past three decades. Whereas in 1978 the primary sector accounted for 28.2% of GDP, it had declined to 10.1% in 2010. In that time education has been upgraded, with nine years of education now universally compulsory. Further economic transformation will require even more investment in human capital.

At the aggregate level, the allocation of labor with various levels of education attainment across sectors has already revealed the minimum requirement of economic transformation on human capital. Table 1 indicates how much more education would be needed if China simply shifts its economy from labor-intensive sectors to capital-intensive sectors in manufacturing and services. As is evident, in the secondary industry (manufacturing) the workers in capital-intensive sectors have more years of schooling than those in labor-intensive sectors. In the tertiary industry (services), the workers in technology-intensive sectors have more years of schooling than those in labor-intensive sectors. This table implies that additional investments in human capital would be required, even without improvement in labor quality within each sector, if there is labor reallocation across sectors. For example, on average 1.3 additional years of schooling would be needed if a worker moves from labor -intensive sectors to capital-intensive sectors in the secondary industry. Once the worker wants to move to the technology intensive sectors in tertiary industry, 4.2 years of schooling would be required. Considering that most sectors demand higher-quality workers over time, the overall demand for human capital to support China's economic transformation will be substantial.

Table 1. Workers' Education Attainment by Industry in Urban China

	The Secondary Industry		The Tertiary Industry	
	Labor Intensive	Capital Intensive	Labor Intensive	Technology Intensive
Composition of education (%)				
Primary and below	17.1	9.4	15.6	1.7
Junior high school	63.7	46.9	50.2	11.9
Senior high school	16.4	30.3	26.4	29.0
College and above	2.9	13.4	7.9	57.4
Years of schooling	9.1	10.4	9.6	13.3

Notes:

The labor-intensive sectors in the secondary industry include textiles manufacturing, manufacture of textile wearing apparel, footwear and caps, manufacture of leather, fur, feather and related products, and manufacture of furniture; capital-intensive sectors in the secondary industry include processing of petroleum, coking, processing nuclear fuel, raw chemical materials and chemical products, manufacture of non-metallic mineral products, smelting and pressing of ferrous metals, smelting and pressing of non-ferrous metals, manufacture of metal products, manufacture of electrical machinery and equipment, and manufacture of communication equipment, computers and other electronic equipment.

In the tertiary industries, labor-intensive sectors include retail and wholesale, hotel and catering services, and services to households and other services. Technology-intensive sectors in the tertiary industry include information transmission, computer services, software, banking, securities, business services, and scientific services.

Source: Authors' calculation from 1% Population Sampling Survey in 2005.

The changing demand for human capital in the near future seems clear. But the necessary structural changes may not be automatic if firms are not responsive to changes on the supply side. Lack of such responsiveness is evident in the growing 'mismatch' between the increased supply of college graduates and the available demand for such skills. The result has been frustration and unemployment. For this reason, in the sections which follow we focus on demand for human capital by firms and how they respond to price changes for both skilled and unskilled workers.

Human Capital Demand at the Firm Level

Industrial upgrading is the aggregation of technological changes by firms and related aggregated demand for skills. In this section, taking advantage of the firm survey data, we look at what types of firms demand skilled workers. We distinguish between two different types of labor input by classifying them as production workers and management workers. We also asked the percentage of production worker with university degrees and the percentage of managers with high school education or above. These two variables make it possible for us to measure the quality of labor input more accurately.

In what follows, we classify labor inputs by several firm characteristics: by firm size, the labor intensity of technology, labor productivity, production efficiency, openness, as well as by sector. These dimensions help us to define those firms with high demand for skills.

Firm Size

Firm size may be correlated with the demand for human capital for several reasons. First, large firms are more likely to have complicated structures that require more human capital to operate. Second, different firm sizes are associated with different technology, inducing demand for different types of human capital. Third, studies of the relationship between firm size and efficiency (Jovanovic, 1982; Brown and Medoff, 1989) indicate a relationship between firm size and demand for human capital since the latter is a determinant of firm efficiency.

In table 2, the firm size is measured in three ways: by total employment, total sales, and the net value of fixed assets. For each indicator, we sort all the firms by these indicators and divide them into five groups. Then we look at the labor input by group. In addition, a t test statistics of equality between the bottom 40% and the top 40% of firms by size is reported.

Table 2 presents the managers with university degrees by firm size and table 3 shows the production workers with high school education by firm size. The trend of labor input and firm size seems quite clear. With increasing size, the firms tend to iuse more human capital in both production and management. All the t-test statistics rejected the null hypothesis of equality between bottom group and top group by size, which strengthens our observation.

This description suggests that, with industrial upgrading, if the firms move toward bigger size in the future, they would demand more human capital.

Table 2. Managers with university degree by the firm size

Group	Mean (St. Dev)	Group	Mean (St. Dev)	t test statistics of equality
By total employment				
20-	39.8 (32.2)	0~40	39.5 (30.9)	
20~40	39.3 (29.6)			
40~60	41.4 (31.7)			4.70
60~80	41.7 (29.0)	60~100	47.9 (29.9)	
80+	54.0 (29.6)			
By total sales				
20-	35.7 (31.2)	0~40	38.1 (31.5)	
20~40	40.4 (31.8)			
40~60	39.3 (29.6)			6.77
60~80	46.2 (29.5)	60~100	50.6 (29.7)	
80+	54.9 (29.2)			
By fixed assets				
20-	35.9 (31.0)	0~40	36.8 (30.7)	
20~40	37.7 (30.5)			
40~60	43.2 (30.0)			7.28
60~80	46.6 (29.7)	60~100	49.8 (29.9)	
80+	53.0 (29.9)			

Source: Authors' calculation from Enterprise Survey in 2009.

Table 3. Production workers with high school education by firm size

Group	Mean (St. Dev)	Group	Mean (St. Dev)	t test statistics of equality
By total employment				
20-	45.5 (25.5)	0~40	46.0 (26.2)	
20~40	46.4 (26.9)			
40~60	45.6 (26.8)			2.13
60~80	48.1 (25.9)	60~100	49.2 (25.6)	
80+	50.2 (25.3)			
By total sales				
20-	44.7 (26.5)	0~40	45.8 (26.9)	
20~40	46.8 (27.2)			
40~60	43.5 (26.1)			2.78
60~80	49.1 (25.7)	60~100	50.2 (26.2)	
80+	51.3 (25.3)			
By fixed assets				
20-	44.1 (26.7)	0~40	45.0 (26.5)	
20~40	45.9 (26.3)			
40~60	45.7 (25.4)			3.29
60~80	47.3 (25.4)	60~100	50.1 (25.6)	
80+	52.9 (25.5)			

Source: Authors' calculation from Enterprise Survey in 2009.

Capital-labor ratio

The ratio of capital to labor indicates the relative capital-intensity of production factors employed by the employers. In general, the firms with high capital-labor ratios tend to have high demand for skilled workers. As Table 4 shows, the management workers with university degree account for 37.9 percent of the group at the bottom 20 percent of the firms in terms of the ratio while the share is 48.7 percent if we look at the top 20 percent of the firms. Looking at the t test of the equality of the share with university degree between the lowest 40 percent and highest 40 percent group, the null hypothesis of equality is rejected, which means that more capital intensive firms demand for more human capital. The other measure of human capital input, the share of production worker completed high school, reflects the same trend.

According to the two rounds of economic census, the average value of fixed assets per worker in manufacturing is RMB 84.7 thousand in 2004 and 163.7

thousand in 2008. A significant trend of intensifying the capital use is found between the two years implying that with higher capital intensity more human capital is demanded.

Table 4. Demand for human capital by the ratio of capital to labor

Group	Mean (St. Dev)	Group	Mean (St. Dev)	t test statistics of equality
Managers with university degree				
20-	37.8 (30.1)	0~40	39.5 (30.2)	4.71
20~40	41.1 (30.3)			
40~60	42.1 (30.9)			
60~80	47.3 (30.9)	60~100	48.0 (30.8)	
80+	48.7 (30.7)			
Production workers with high school education				
20-	44.7 (26.7)	0~40	44.4 (26.5)	3.29
20~40	44.2 (26.4)			
40~60	47.5 (26.2)			
60~80	49.2 (24.6)	60~100	49.5 (25.3)	
80+	49.8 (26.1)			

Source: Authors' calculation from Enterprise Survey in 2009.

The ratio of value added to gross output

The ratio of valued added to gross output measures firms' production efficiency. As noted earlier, there is large disparity in terms of the ratio of value added to gross output between China and the economies with advanced manufacturing. If we look at the share of management workers with university degree and the share of production workers with high school completion by group, as in Table 5, no clear trend of mean value of skills is found by the ratio of value added to gross output between quintiles. In the bottom 40% of firms by ratio of value added to gross output 44.2 % of mangers have a university degree and 46.4 % of production workers have high school education or above. The corresponding proportion for the top 40% of firms are 46.4% and 48.6% respectively. However, neither for managers nor for production workers, the t test statistics of equality between top 40% and bottom 40% can reject the null hypothesis.

Table 5. Demand for human capital by the ratio of value added to gross output

Group	Mean (St. Dev)	Group	Mean (St. Dev)	t test statistics of equality
Managers with university degree				
20-	45.8 (31.1)	0~40	44.2 (31.3)	1.18
20~40	42.7 (31.4)			
40~60	39.3 (29.8)			
60~80	44.0 (30.7)	60~100	46.6 (30.8)	
80+	49.4 (30.6)			
Production workers with high school education				
20-	49.7 (26.2)	0~40	46.3 (25.4)	1.33
20~40	43.1 (24.2)			
40~60	46.1 (26.6)			
60~80	47.5 (27.2)	60~100	48.6 (26.7)	
80+	49.7 (26.2)			

Source: Authors' calculation from Enterprise Survey in 2009.

Labor productivity (value added per worker)

Table 6 analyzes the two variables by the firms grouped by labor productivity, measured by value added per worker. As indicated in the table, the bottom 20% firms measured by labor productivity have 33.7% of managers with university degree and 44.9% of production workers with high school education while the two shares are 49.2% and 49.4% for the top 20% firms. In addition, the t test statistics of equality between the top 40% and bottom 40% of firms reject the null hypothesis. It seems that the descriptive statistics reveals the trend that demand for skills increases with the labor productivity. This is not a surprising result that skilled workers are more productive than unskilled workers in production.

Table 6. Demand for Human Capital by labor productivity

Group	Mean (St. Dev)	Group	Mean (St. Dev)	t test statistics of equality
Managers with university degree				
20-	37.7 (31.0)	0~40	40.4 (31.2)	3.37
20~40	43.1 (31.3)			
40~60	42.6 (29.9)			
60~80	44.6 (30.9)	60~100	46. (31.0)	
80+	49.2 (30.8)			

Production workers with high school education				
20-	44.9 (26.4)	0~40	45.7 (26.1)	2.09
20~40	46.6 (25.7)			
40~60	46.3 (25.8)			
60~80	48.8 (25.7)	60~100	49.1 (26.1)	
80+	49.4 (26.6)			

Source: Authors' calculation from Enterprise Survey in 2009.

Openness

Studies of the relationship between openness and demand for skilled labor assume that skilled labor is needed to adapt managerial, organizational and technical innovations brought about by inflows of FDI or by external demand. Openness is also associated with technological diffusion, which in turn induces the demand for skills. However, if an economy is specialized in labor-intensive industries, the demand for unskilled workers will be dominant. That is why the empirical findings are mixed across countries. For example, Fajnzylber and Fernandes (2004) find that openness is associated with an increased demand for skills in Brazil, but not in China. Using firm level data set across eight countries, Almeida (2009) shows that greater openness and technology adoption have increased the demand for skills, especially in middle income countries, but China is also an exception in her study for reasons we suggest below.

The descriptive statistics of our data is consistent with observations in existing studies. The share of production workers with high school or above is 45.3% in exporter firms, but the share is 48.1% in firms that do not export. The t test statistics reject the null hypothesis of equality between the two sectors. For managers, however, the exporters tend to demand for more skills, as evidenced by Table 7.

Table 7. Demand for skills between domestic and export-oriented sectors

	Exporter	Non-Exporter	t test statistics of equality
Managers with university degree	49.0 (31.0)	41.3 (30.7)	4.24
Production workers with high school education	45.3 (26.5)	48.1 (26.3)	1.80

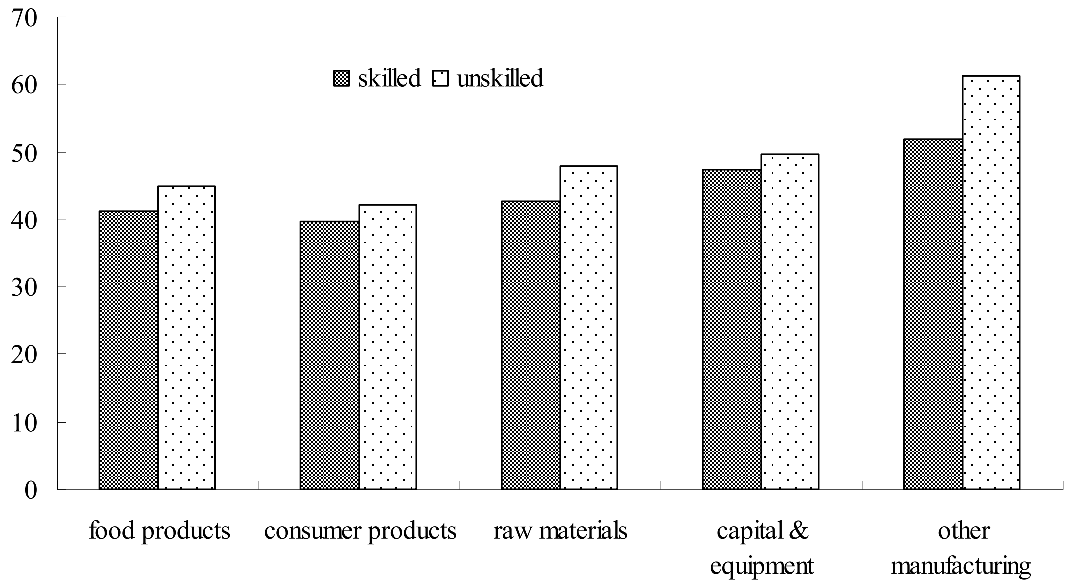
Source: Authors' calculation from Enterprise Survey in 2009.

As discussed, if the export-oriented firms are specialized in labor-intensive sectors, it is not surprising that they use more unskilled workers. Meanwhile, even the firms faced with shortages of unskilled workers and growing labor costs are subject to the available supply of skilled workers when the firms wish to change their technologies. This mismatch helps in part to explain why labor-intensive sectors are still dominant in the Chinese economy even if China has already been facing with growing labor costs. In other words, the reason China is an exception in the studies cited above is because it is still in the earlier stages of a transition.

Sector

We categorized the sub-sectors of manufacturing into six groups, food products, consumer products, raw materials, capital and equipment, and other manufacturing. Figure 2 presents the quality of labor inputs by sector. For both indicators measuring the labor quality, they show the same trend across sectors. The firms in capital and equipment manufacturing use labor with most humn capital while the firms in food products and consumer products employ less-skilled workers. This pattern is consistent with the above description since the firms in capital and equipment are the large, capital-intensive, and more productive ones.

Figure 2. the quality of labor input by sector



Source: Authors' calculation from Enterprise Survey in 2009.

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Summary

In this section, we have studied the quality of labor input demanded by firms according to a variety of firm characteristics. As China moves towards a more value-added economy, it will first need to realize adjustments of labor input at the firm level. The descriptive statistics in this section have indicated that the demand for skills is associated with particular firm characteristics: large capital- intensive and productive firms demand more skills. They could be export-oriented firms, but those tend to demand high human capital demand among managers rather than workers. Looking at sectoral differentials, however, we found differences in demand for skills to be insignificant. Nor is the demand for skills associated with production efficiency.

Model of Firm Demand for Human Capital

Following Roberts and Skoufias (1997), each firm's production function can be represented by a value-added function. Among the inputs, skilled labor and unskilled labor are assumed as two different inputs, which allow them to have different coefficients in the production function. Each firm chooses its combination of capital and labor inputs to minimize the cost of producing a planned level of output Q*. This gives rise to the demand function as what follows for both skilled and unskilled workers as well.

$$\ln L_i^j = \alpha_0 + \alpha_1^j \ln Q_i^* + \alpha_2^j \ln w_i^j + \alpha_3^j \ln rw_i + \beta_1^{j,k} \sec t_i^k + \beta_2^{j,l} ow_i^l + \beta_3^{j,m} city_i^m + \beta_4 age_i + \varepsilon_i^j$$

(1)

The left hand side variable, $\ln L_i^j$ is the logarithm of employment in firm *i* where j denotes the type of the workers, production workers or management workers (j=1 for unskilled workers and 2 for skilled workers). The right hand side variables include $\ln Q_i^*$ logarithm of planned value added, $\ln w_i^j$ logarithm of monthly salary for production or management workers, $\ln rw_i^j$ logarithm of ratio of wages of management workers to production workers, and a group of observable firm characteristics that approximate the production technology. $\sec t_i^k$ is a set of dummies of the sub-sectors to capture the variations of technology across sub-sectors in manufacturing. ow_i^l is a set of ownership dummies controlling for the potential technology differences among firms with different ownerships. $city_i^m$ is the dummies indicating the locality of the firms and capture the factors affecting choice of technology and associating with location. The city dummies may also capture the local labor market characteristics. The firm's age (age_i) controls for vintage effects in the firm's technology as well as for differences in form efficiency as discussed by Jovanovic (1982) and Liu and Tybout (1996). ε_i^j is the error term.

The appropriate specification depends on the source of the error term in equation (1). There are several potential sources of error. The first is firm heterogeneity, which can arise from the non-observability of some key inputs in the production process. Given the cross section data are employed here, we try to eliminate this firm heterogeneity by controlling for the firm characteristics as discussed above.

The second source of error arises from fluctuation in output as a result of unforeseen fluctuations in demand, like negative shock from global financial crisis, factor supplies, or reporting errors. As we see from equation (1), the appropriate output variable included is the planned output $\ln Q_i^*$. In the case that the firm does not respond these random shocks, the observed output may not be a good measurement on which the employment decisions are based. In addition, the estimator is subject to simultaneity problems when profit-maximizing firm jointly chooses both output and labor inputs (Griliches and Mairesse, 1995). As a result of output measurement error, OLS estimator will tend to bias the responsiveness of employment to both wage and output changes.

To correct the possible correlation between the observed output and the error term, we utilize instrument variable estimators. This requires an instrument that is correlated with the planned output but uncorrelated with the random fluctuations to the output. To satisfy the requirement, we use the net value of fixed asset of the firm in 2007 as well as whether the firm is exporter right before global financial crisis as instruments.

Empirical Results

The results for 2SLS estimator are reported in Table 8, including the first and second stage regression. The validity of the instrumental variable (IV) estimation hinges on two main assumptions: i) exogeneity of instruments with respect to dependent variable; and ii) relevance of the instruments (correlation with the instrumented variable). There are several tests which are conducted to determine the validity and adequacy of the instruments we used. Three tests are reported here.

First, the Sargan test is to test the over-identifying restrictions. The null hypothesis of this test is that the two instruments are valid. As shown in table 8, the Sargan test statistics can not reject the null hypothesis, which supports our selection of instruments.

The second concern about the validity of the instruments is whether the instruments are only weakly identified in our specification. According to Stock et al. (2002), various procedure are available for detecting weak instruments in linear IV model by looking at several statistics in the first-stage regression: The first-stage F-statistics must be greater than a threshold. As a rule of thumb F must be bigger than 10; The first-stage t-statistics as a rule of thumb must be greater than 3.5; The first stage R^2, greater than 30 percent. In table 8 the results for the two equations meet or are closed to these conditions. The first stage F statistics for both equations is greater than 10. The first stage R^2 is 0.28. In addition, Cragg-Donald Wald F statistics reject the null hypothesis of weak identification, which means that our instruments are not weakly identified.

Third, the under-identification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors, here the observed output of the firm. The Anderson LM statistics reject the null hypothesis that the equation is under-identified, which means our instruments are correlated with the instrumented variable.

Table 8. Labor Demand by Skill Group: IV Estimators

	Unskilled Labor		Skilled Labor	
	Coeff.	t	Coeff.	t
First-Stage Regression: endogenous regressor is lnQ				
$\ln w_i^j$	1.11	3.83	1.10	3.79
Relative Wage (skilled/unskilled)	1.07	3.17	-0.065	-0.17
Age of the Firm	0.026	3.07	0.026	3.06
Sectors (reference to Food Products)				
Consumer Products	-0.087	-0.32	-0.091	-0.33
Raw Materials	-0.34	-1.29	-0.35	-1.33
Capital & Equipment	0.067	0.23	-0.086	-0.30
Other Manufacturing	-0.39	-1.04	-0.40	-1.07
Ownership (reference to State & Collective)				
Private & Joint	-0.048	-0.11	-0.061	-0.14
Ltd	-0.00	-0.00	-0.01	-0.02
Foreign & Other	-0.30	-0.64	-0.26	-0.55

City dummies	Yes		Yes	
Asset in 2007	0.56	12.21	0.57	12.11
Export in the first half 2008	0.52	2.75	0.51	2.65
Summary results for first-stage regressions				
F statistics	15.23	*P*-val=0.00	14.69	*P*-val=0.00
R^2	0.28		0.28	
Under-Identification Test (the null hypothesis: the equation is under-identified)				
Anderson LM statistic	169.7	*P*-val=0.00	148.1	*P*-val=0.00
Weak Identification Test (the null hypothesis: the equation is weakly identified)				
Cragg-Donald Wald F statistic	82.66	*P*-val=0.00	80.83	*P*-val=0.00
The Second Stage Regression				
Log of value added	0.80	12.86	0.77	12.59
$\ln w_i^j$	-0.51	-2.04	-0.48	-1.96
Relative Wage (skilled/unskilled)	-0.74	-2.63	-0.34	-1.15
Firm Age	-0.004	-0.56	0.002	0.31
Sector (reference to Food Products)				
Consumer Products	0.55	2.54	0.24	1.14
Raw Materials	0.35	1.68	0.30	1.48
Capital & Equipment	0.19	0.84	0.22	0.97
Other Manufacturing	0.36	1.23	0.70	2.42
Ownership (reference to State & Collective)				
Private & Joint	0.13	0.40	-0.26	-0.80
Ltd	0.13	0.39	-0.18	-0.55
Foreign & Other	0.34	0.93	0.026	0.07
City dummies	Yes		Yes	
Sargan Over-identification test	0.029	*P-Val* = 0.86	0.21	*P-Val* = 0.65
No. of Observations	1393		1373	

The coefficients of interests here are α_r^j (r=1, 2, 3; j=1, 2). They are labor demand elasticity with respect to output, own-wage, and relative wage between skilled and unskilled workers respectively. Except for the skilled labor demand elasticity with respect to the relative wage, the other coefficients are statistically significant. Table 9 gives both the OLS and the IV estimates. As we see, the OLS underestimates the employment responsiveness to output changes and the direction of response to wage is inconsistent with theory and most empirical results (Hamermesh, 1993). These results suggest that output measurement error is a significant source of bias in OLS estimates of the wage and output elasticities. Therefore, our discussion is based on IV estimators.

According to IV estimates, the employment elasticity to output is 0.80 for unskilled workers and 0.77 for skilled workers. In the study on Colombia, Roberts and Skoufias (1997) report that the instrumental-variables estimates of the output elasticity for skilled and unskilled workers are 0.894 and 0.755, respectively. Our results imply that skilled and unskilled employment increases with the size of firm increases. In contrast, as moving toward larger firms, measuring by output, employment of skilled labor increases at slightly slower rate than unskilled labor.

The own-price elasticity is -0.509 for unskilled workers and -0.482 for skilled workers. A higher price elasticity in magnitude for unskilled labor implies that an equal proportional increase in the costs of each type of worker result in a larger decline in the employment of unskilled workers. This comparison is particularly relevant to contemporary China, where the manufacturing sectors are suffering from more and more serious shortage of unskilled workers and increasing wages. For example, in 2011 the average monthly salary for migrant workers increased 15% in real term over the previous year. This trend will certainly reduce the employment demand for unskilled workers.

Our specification also includes the relative wage of managers to production workers and the estimates give the elasticity of unskilled and skilled workers with respect to the relative wage. According the elasticities based on IV estimates, the relative-wage elasticity for unskilled workers is -0.741, which implies that a growing wage difference between skilled and unskilled workers may decrease the demand for unskilled workers quite substantially. This observation is consistent with the fact that growing shortage and rising wages of unskilled workers now. In addition, if the technological changes keep biased to skills, wage growth may bias to skilled workers too. If this is the case, the employment loss for unskilled workers could be a matter.

As shown in the regression results, the relative-wage elasticity for unskilled workers is not statistically significant.

Table 9. Summary of Demand Elasticities

	Unskilled Workers		Skilled Workers	
	OLS	IV	OLS	IV
Output elasticity	0.143	0.796	0.140	0.769
Own-Wage elasticity	0.606	-0.509	0.581	-0.482
Relative-Wage elasticity	0.268	-0.741	-0.462	-0.343

Conclusions

The Chinese labor market has witnessed a great change in recent years, as evidenced by growing labor costs and frequent labor shortage. With these labor market changes, employers are widely concerned about shrinking advantages in labor costs. At the aggregate level, it would be possible for China to be less competitive in tradable sectors if capital and technology substitutions for labor fail to occur.

Based on the experiences of other economies, rising labor costs will encourage upgrading in the Chinese economic structure. But the desired transformation of growth pattern will not take place automatically in the absence of certain conditions: first, that firms respond to changes in relative prices and second, that supplies of human capital respond to changing demand for skills.

Taking advantage of the recent PBC firm survey data, the empirical results in this paper indicate that the firms in manufacturing sectors are quite responsive to changes in labor market conditions. For both skilled and unskilled workers, the own-wage labor demand elasticities are quite substantial in magnitude.

But it is also important to note that China is at 'crunch time' to adapt to the changing labor market and economic transformation. On the demand side, the shift away from unskilled workers towards skilled workers is expected market behavior although some firms might fail to survive during the transition. However, the policy makers' responses to these changes are important. If policy makers insist on subsidizing firms such as state owned enterprises in multiple ways, market prices will be distorted and hinder the needed economic adjustments. At the same time China needs more reforms at the firm level in order to encourage firms to anticipate and respond to the factor changes.

With respect to the supply of skills, our research suggests China faces inevitable increased demand for more skilled labor. These supplies cannot be provided by firms themselves; instead public policy intervention is desirable to provide the 'public goods' of higher education which will benefit the society as a whole. China not only needs to invest more in human capital through public resources, but needs to reform this human capital accumulation system so as to make it more efficient.

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Appendix

Descriptive Statistics

Ownership type (%)		
	State/collective	3.8
	Private	29.0
	Joint/Ltd/Other	52.5
	Foreign	14.7
Province (%)		
	Zhejiang	29.6
	Jiangsu	16.1
	Guangdong	13.6
	Shangdong	18.3
	Jilin	4.6
	Hubei	2.8
	Shaaxi	8.6
	Sichuan	6.4
Exporter (%)		25.9
Industrial Sector (%)		
	Food Products	11.4
	Consumer Products	27.7
	Raw Materials	31.8
	Capital & Equipment	22.8
	Other	6.2