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RETURNS TO EDUCATION OF MANUFACTURING WORKERS: EVIDENCE FROM THE PEOPLE'S REPUBLIC OF CHINA EMPLOYER–EMPLOYEE SURVEY

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We would like to thank the participating firms and employees who welcomed CEES enumerators to their firms and completed the survey in 2015 and 2016.

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Abstract

Drawing on a random-sampling of matched employer–employee data that was collected in 2016 by the People's Republic of China Employer–Employee Survey, we first estimate returns of education for Chinese manufacturing workers. Using hourly wages as the dependent variable, we find that the estimated return to schooling was 5.1% within each firm, which is lower than that estimated by most recent studies based on the People's Republic of China's urban household survey data and the Chinese Population Census. After including education dummy variables in our regressions, we find that low returns to high school and vocational college are important factors to explain the low returns to education for Chinese manufacturing workers. Our between-group comparisons also show that educational inequality in less-developed regions and falling returns to female education are possible contributing factors to low returns to education. In addition, if the omitted ability characteristics can be fully controlled, then the true returns to education for Chinese manufacturing workers may become lower.

Keywords: education, manufacturing workers, employer-employee survey, People's Republic of China

JEL Classification: I26, I25, E24

Contents

1. INTRODUCTION

Although many papers have estimated the returns to education using Chinese data, their findings are often inconsistent (e.g., Zhang et al. 2005; Giles, Park, and Wang 2008; Li, Liu, and Zhang 2012; Li, Liang, and Wu 2016; Li et al. 2017a). On the one hand, some papers have found that returns to education in the People's Republic of China (PRC) have risen rapidly since the 1980s, from only 2%–4% in the 1980s to nearly 10% in the early 2000s (Fleisher and Wang 2005; Heckman and Li 2004; Zhang et al. 2005; Li et al. 2012).[1] To investigate the reasons for the observed rising returns to education, some studies have found that demand effects (e.g., the reform of labor market institutions, skill-biased technical change, and globalization) are main factors resulting in rising returns to education (Li et al. 2017b; Zhang et al. 2005). On the other hand, other studies have found that the returns to education in the PRC are still relatively low. For example, Li, Liu, and Zhang (2012) collected twin data from urban PRC and found that the estimated return to years of schooling was reduced to 2.7%, using a within-twin fixed-effects model to control for individual ability and family background. Some studies ultimately found that supply effects (e.g., the PRC's highly selective and exam-oriented education system, insufficient incentives to improve educational quality due to the government's emphasis on growth, and the PRC's decentralized fiscal system) are the main factors resulting in low returns to education (e.g., Zhang 2009; Li, Liu, and Zhang 2012; Wong 1997; Huang, Rozelle, and Wang 2006).

One explanation for this division within the literature may lie in the limitations of the Chinese individual-level datasets that these articles used. To date, most papers have analyzed individual-level data from sources such as the PRC's urban household survey and the Chinese Population Census to estimate returns to education. However, these datasets sampled individuals with households as the sampling frame, and they do not include the employment status of the workers in the labor market. Furthermore, these datasets only contain individual-level data and they lack any detailed information on the workplace. Thus, it is difficult to use this data to control for sorting effects, which are correlated both with the individual's earnings and their education.

Despite these data limitations, there are still rare studies that have attempted to estimate returns to education for Chinese manufacturing workers, and for good reason. Today, the PRC has become the "world's factory." In 2017, 205 million workers were employed in the PRC's manufacturing sectors, accounting for 28% of the global manufacturing labor force. Although the Chinese manufacturing sectors have grown rapidly since the PRC's economic reform began in 1978, they also face major challenges, such as rising labor costs and a declining working-age labor force (Li et al. 2012; Li et al. 2017). Considering that the end of cheap, low-skilled workers may be approaching, the PRC should accelerate human capital accumulation to increase efficiency within its manufacturing sectors. Given that returns to education provide important information about the incentives for human capital investment, estimating these returns is of great value in understanding the economic transition of this "world factory."

[1] The low estimated returns to education were found in some studies using data from urban PRC from the 1980s and 1990s (Byron and Manaloto 1990; Meng and Kidd 1997).

Drawing on data from the People's Republic of China's Employer–Employee Survey (CEES), which is a new longitudinal study of manufacturing firms and workers in the PRC, we begin by estimating returns to education for Chinese manufacturing workers. The CEES dataset has several advantages. First, the CEES randomly samples workers from various firms in the PRC, which creates a sample that is more representative of the PRC's manufacturing sector. Second, this survey not only contains data at the employee level but it also contains detailed firm level information. This matched employer–employee survey data allows us to sufficiently control for sorting effects, which can otherwise result in bias in the estimated returns to education for manufacturing workers.

Based on the CEES data, our paper finds that the returns to education for Chinese manufacturing workers are lower than the most recent estimates using the PRC's urban household survey and the Chinese Population Census (e.g., Zhang et al. 2005; Li et al. 2012). When adding firm fixed effects into our regressions, with monthly earnings (hourly wages) as the dependent variable, the estimated within-firm return to schooling is 3.9% (5.1%). Although our estimates are lower than the estimates of those studies that claim that the value is nearly 10%, our estimates of returns to schooling are similar to those of recent studies using twin data (Li, Liu, and Zhang 2012), which find that the returns to schooling only reach 2.7% using within-twin fixed effects.

Our estimates incorporate different levels of education and between-group comparisons, and therefore shed light on some possible explanations for the low returns to education for Chinese manufacturing workers. First, we find that returns to academic high school (vocational college) are lower than those for vocational high school (university). The low returns to high school may be due to the Chinese education system's emphasis on examination preparation at the expense of developing the knowledge and skills that are needed for the workplace (Han and Yang 2001; Zhang 2009; Li, Liu, and Zhang 2012). The low returns to vocational college may be due to the inequality of education resources because the PRC's government has invested most of its resources in universities, while vocational colleges remain under-served.

Second, our subsample regressions find that returns to education in developed regions are significantly higher than those for less-developed regions, while returns to female education are not significantly higher than those for male education. These results suggest that poor education quality and the decreased returns to female education may contribute to the overall low returns to education for Chinese manufacturing workers.

Third, our analysis of CEES data finds that the estimated returns to schooling for migrant workers are significantly higher than those for local workers. Without including variables to control for ability bias in regression, the higher within-firm returns to education for migrant workers may be due to their higher ability. Therefore, our findings suggest that if omitted ability can be sufficiently controlled, then the true returns to education for Chinese manufacturing workers may become even lower.

The rest of this paper is structured as follows. In Section 2, we present our econometric models. In Section 3, we introduce the CEES dataset and we report our descriptive results. Section 4 presents our main results on estimates of both returns to schooling and returns to different levels of education. Section 5 reports on our between-group comparisons. Finally, we discuss the implications of our findings and conclude our discussion in Section 6.

2. ECONOMETRIC SPECIFICATION

2.1 Returns to Schooling

To estimate the returns to schooling for Chinese manufacturing workers, we estimate a semi-logarithmic specification for earnings given by:

$$lny_i = \beta_0 + \beta_1 Schooling_i + \beta_2 Male_i + \beta_3 Age_i + \beta_4 Age_i^2 + \mathrm{Z}_i'\gamma + \gamma_m + \varepsilon_i \quad (1)$$

where subscript *i* represents individual, and subscript *m* represents firm (j), industry (d), and county (c), respectively. The dependent variable, lny_i, represents one of three outcome measures that will be used in estimating returns to schooling.

The first outcome variable that we used in the regression is the log of monthly earnings, which is defined as the sum of wages and bonuses that an individual worker can earn in one month. Our second outcome variable is the log of individual working hours per month. According to existing studies, labor market participation may be distributed unevenly among workers of different education levels (Zhang et al. 2005; Bick, Fuchs-Schundeln, and Lagakos 2018). Thus, if better-educated workers are inclined to work fewer hours, then using only monthly earnings as our dependent variable would underestimate returns to schooling. The third variable that we used in estimating returns to schooling is the log of individual hourly wage; that is, the wages that a single worker can earn within one hour. Therefore, the hourly wage eliminates the effects of labor market participation on earnings. Compared to monthly earnings, with the hourly wage as the dependent variable, we can obtain more accurate estimates of returns to schooling.

On the right-hand side of our regression equation, the key independent variable $Schooling_i$ is educational attainment measured as years of schooling. Our parameter of interest in estimating returns to schooling is β_1. $Male_i$ is a dummy variable capturing differences in outcome variables between men and women. To control for non-linear relationships between income (working hours) and work experience, we include individual age (Age_i) and its square (Age_i^2) in the equation (1).

To isolate the effect of years of schooling on income and working hours, we need to control for a series of variables that may be correlated with both education and our dependent variables. These controls are represented by the control vector Z_i in equation (1). This vector includes measures such as individual marital and *hukou* status. It also includes a dummy variable, $migration_i$, which is one (zero) for migrant (local) workers. Next, because better-educated workers are more likely to be sorted into higher-paying workplaces, we include variables representing fixed effects for two-digit industrial sectors (γ_d), counties (γ_c) and firms (γ_j) in equation (1). As a result of controlling for these job-related variables, the parameter of interest (β_1) for estimating returns to education is expected to be lower than those excluding these fixed-effects. It is of note that with the CEES data used in this paper, we can estimate within-firm returns to schooling after controlling for firm fixed effects, which represents a departure from those existing papers that rely solely on individual survey data (i.e., Zhang et al. 2005; Giles, Park, and Wang 2008; Li, Liu, and Zhang 2012; Li, Liang, and Wu 2016; Li et al. 2017).

2.2 Returns to Different Levels of Education

Some previous papers find that returns to education may differ across education levels (Li, Liu, and Zhang 2012; Li et al. 2017). To measure these differences, we estimate the following econometric equation:

$$lny_i = \alpha_0 + \alpha_1 H_i + \alpha_2 VH_i + \alpha_3 VC_i + \alpha_4 C_i + \alpha_5 Male_i + \alpha_6 Age_i + \alpha_7 Age_i^2 + Z_i'\gamma + \gamma_m + \nu_i \quad (2)$$

In this equation, all variables except those dummies for different education levels are consistent with those in equation (1), which have been explained previously.

The key independent variables in this equation are four dummies that are used as measures of education—high school (H_i), vocational high school (VH_i), vocational college (VC_i) and university (C_i)—with students in junior high school or below used as the control group. Each education dummy is defined in the same fashion, with its value being equal to one if the education level it represents is the highest level that an individual has obtained, and is zero otherwise. For example, the high school dummy equals one if the last qualification that an individual obtained was a high school qualification, and is zero otherwise.

3. SURVEY AND DATA

In this section we will briefly describe the 2015 and 2016 CEES that we have used in this paper. We also summarize the key variables for our empirical analysis.

3.1 The People's Republic of China Employer–Employee Survey

The CEES is a new longitudinal study of manufacturing firms and workers in the PRC that was conducted by the authors. The CEES began in 2015 with a survey of firms and workers in the PRC's most important industrial province, Guangdong, which at that time accommodated 300,000 manufacturing firms (13.4% of all manufacturing firms in the country) and 20.6 million manufacturing workers (16.5% of all manufacturing workers), and accounted for a remarkable 25.9% of the nation's international trade (imports and exports amounted to $1.1 trillion). In 2016, we followed up with the firms and workers that were surveyed in Guangdong in 2015 and new workers were added to the employee sample for this province. Then, to capture differences between workers in Guangdong and those in the PRC's emerging central region, a second province, Hubei, was added in 2016. In 2015, Hubei province produced $708.3 billion in gross industrial output and it employed 3.4 million manufacturing workers.[2]

[2] The third round of the survey was launched in July 2018, and we added three new provinces in CEES: Jiangsu, a relatively developed province in East PRC; Sichuan, an emerging province in West PRC; and Jilin, an important province in Northeast PRC. In total, these three provinces produced $3,288 billion in gross industrial output and employed 21.7 million manufacturing workers in 2015.

Lists of firms from the third National Economic Census that was conducted in 2014 were used as the sampling frame for this survey in 2015 and 2016.[3] Sampling was conducted in two stages, each using probability proportionate-to-size (PPS) sampling. We defined size as the number of employees involved in manufacturing. Thus, the firm sample is representative of the employment size of firms in the PRC. In the first stage, 20 county-level districts were randomly sampled in each province, with probabilities proportionate to manufacturing employment size in each district. In the second stage, 50 firms were sampled in each district as a target sample, again with probabilities proportionate to employment in each firm. Enumerators then visited the 50 firms in sequence and attempted to survey the first 36 eligible firms (i.e., those that had production activities in the sampled district).

Employees were also randomly selected with stratification. We first asked firms to provide a list of all of the employees on record at the end of the previous year, with middle and senior managers listed separately. We then randomly selected 10 employees from each firm (six to nine for smaller firms), among which three (two for smaller firms) were middle and senior managers. If the selected employees could not participate (e.g., they were not working on site during the survey period), then they were replaced with the workers whose employee identification numbers were closest to theirs on the list of workers. This process was carried out until the targeted number of sampled employees was reached. In total, these two survey rounds collected data from 573 firms in Guangdong in 2015, and 1,122 firms from both Guangdong and Hubei in 2016 (Table A1). We had response rates of over 80% for both years.

The firm and worker questionnaires that we used in this study were designed by the authors together with a team of over 30 researchers. The 2016 worker questionnaire includes five modules and 443 variables, covering personal background (including education level, years of schooling, gender, age, marital status, *hukou* and migration), current job, work history, social security, and personality traits. The 2016 firm questionnaire includes seven modules and 1,030 variables, covering the basic situation of the firms, firm-head characteristics, management, production, sales, innovation, quality control, and human resources.

3.2 Data Summary

A summary of the earnings and education measures is reported in Table 1. First, based on CEES data, we find that the average monthly earnings for Chinese manufacturing workers in 2016 was RMB 3,774 ($581), which is higher than those of many emerging economies, including Malaysia ($538 in 2015), Thailand ($438 in 2014), and Mexico ($280 in 2016).

Second, conducting statistical analyzes by province, we find that both earnings and labor participation in developed regions are higher than in developing regions. On the one hand, the average monthly earning (hourly wage) in Guangdong province was RMB 4,055 (RMB 21),[4] which is 17.8% (16.7%) higher than those for Hubei province (with RMB 3,441 and RMB 18, respectively). On the other hand, the average working hour per month in Guangdong province was 205.1, which is 2.8% higher than that for Hubei province (199.7 hours per month).

[3] For the third round of the survey in 2018, the sampling frame was changed to the list of firms from the Annual Report Database in 2016, which was collected by State Administration for Market Regulation (SAMR) in the PRC.

[4] The number in brackets is the average hourly wage.

Third, based on CEES data, the average years of schooling for Chinese manufacturing workers in 2016 was 12 years. This is 0.2 years greater than the 11.8 years found using the PRC's urban household survey in 2001 (Zhang et al. 2005), and 2.4 years greater than the 9.6 years found using the Chinese Population Census for the adult labor force (ages 25–64) in 2015 (Li et al. 2017). In contrast from the PRC's urban household survey, which excludes all of rural *hukou* workers who are less educated, the results from the CEES show that education has risen rapidly since the early-2000s. Given that the CEES focuses on manufacturing firms and workers in the PRC, the fact that the average years of schooling value from the CEES is higher than that of the adult labor force means that the overall education level of workers in the manufacturing industry is higher than in most of other industries.

Fourth, with our statistical analyzes by province, we also find small differences of education between developed regions and developing regions. The average years of schooling in Guangdong province, in which the GDP per capita was $11,132 in 2016, was 11 years. This is one year less than that of Hubei province (12 years), in which the GDP per capita was $8,452 in 2016. Similarly, about 10% of manufacturing workers in Guangdong in 2016 had received a university education, which is 4 percentage points lower than the average for Hubei (14%). Considering the higher individual earnings in Guangdong, we can expect that returns to education in developed regions are higher.

Table 1: Summary Statistics of Wages, Working Hours and Education Distributions of CEES

	All Firms		Guangdong		Hubei	
	Obs.	Mean (Std.)	Obs.	Mean (Std.)	Obs.	Mean (Std.)
1. Wages and working hours						
Monthly earnings (RMB)	8,373	3,774 (1,941.9)	4,544	4,055 (2,034.2)	3,829	3,441 (1,769.6)
Working hours per month	8,213	202.6 (45.8)	4,452	205.1 (45.4)	3,761	199.7 (46.1)
Hourly wages (RMB)	8,213	20 (15.0)	4,452	21 (17.2)	3,761	18 (11.6)
2. Education						
Years of schooling	8,684	12 (3.0)	4,656	11 (3.0)	4,028	12 (3.0)
High school (0-1 dummy)	8,684	0.20 (0.40)	4,656	0.19 (0.39)	4,028	0.21 (0.41)
Vocational high school (0-1 dummy)	8,684	0.17 (0.37)	4,656	0.16 (0.37)	4,028	0.17 (0.38)
Vocational college (0-1 dummy)	8,684	0.17 (0.37)	4,656	0.16 (0.36)	4,028	0.18 (0.39)
University (0-1 dummy)	8,684	0.12 (0.32)	4,656	0.10 (0.30)	4,028	0.14 (0.35)

Notes: statistical analyses are based on the "China Employer-Employee Survey" (CEES) data.

Table 2 presents the statistical results obtained from earnings, working hours and education by gender and migration status. These figures reveal two important findings. First, male workers are both higher paid and better educated. The average monthly earnings (hourly wage) for males is RMB 4,230 (RMB 22), which is 32.4% (29.4%) higher than that of female workers (RMB 3,196 and RMB 17, respectively). Similarly, the average years of schooling for males is 12 years, which is one year higher than that of females (11 years). We see that 13% (18%) of male workers receive a university

(vocational college) education, which is 3 (2) percentage points higher than the amount attained by females (10% and 16%, respectively).

The second finding of note from Table 2 is that both the earnings and educational attainment of migrant workers are higher than those of locals. The average monthly earnings (hourly wages) of migrant workers is RMB 4,294 (RMB 22), which is 32.0% (29.4%) higher than that of local workers (RMB 3,253 and RMB 17, respectively). Similarly, 15% migrant of workers had received a university education, which is 6 percentage points higher than that of local workers (9%).

Table 2: Summary Statistics of Wages, Working Hours and Education with Gender and Migration Status (CEES Data)

	Male		Female		Migrant Worker		Local Worker	
	Obs.	Mean (Std.)	Obs.	Mean (Std.)	Obs.	Mean (Std.)	Obs.	Mean (Std.)
1. Wages and working hours								
Monthly earnings (RMB)	4,678	4,230 (2,139.7)	3,693	3,196 (1,467.4)	3,868	4,294 (2,117.7)	4,079	3,253 (1,616.3)
Working hours per month	4,586	203.8 (46.5)	3,625	201.0 (44.9)	3,787	205.8 (45.9)	4,010	200.0 (45.3)
Hourly wages (RMB)	4,586	22 (16.0)	3,625	17 (13.0)	3,787	22 (15.5)	4,010	17 (14.0)
2. Education								
Years of schooling	4,822	12 (2.9)	3,860	11 (3.1)	4,012	12 (3.1)	4,245	12 (2.9)
High school (0-1 dummy)	4,822	0.22 (0.42)	3,860	0.17 (0.38)	4,012	0.19 (0.39)	4,245	0.21 (0.41)
Vocational high school (0-1 dummy)	4,822	0.17 (0.38)	3,860	0.16 (0.37)	4,012	0.16 (0.36)	4,245	0.18 (0.38)
Vocational college (0-1 dummy)	4,822	0.18 (0.38)	3,860	0.16 (0.36)	4,012	0.17 (0.37)	4,245	0.17 (0.38)
University (0-1 dummy)	4,822	0.13 (0.34)	3,860	0.10 (0.30)	4,012	0.15 (0.36)	4,245	0.09 (0.29)

Notes: statistical analyses are based on the “China Employer-Employee Survey” (CEES) data.

To save space, Table A2 contains the summary statistics regarding other individual characteristics, such as gender, age, marital and *hukou* status, and migration.

4. RETURNS TO EDUCATION

In this section, based on the CEES data, we report the estimates of returns to education for Chinese manufacturing using regression analyzes.

4.1 Estimates of Returns to Schooling

Table 3 contains our estimates of returns to schooling with the monthly earnings as the dependent variable. As shown by column 1 in Table 3, without controlling for fixed effects or differences in main individual characteristics (e.g., marriage, *hukou*, or migration status), the raw return to schooling is 4.1%, which is significantly lower than the estimates of most prior studies using Chinese or Asian data, which reach nearly 10% (e.g., Heckman and Li 2004; Zhang et al. 2005; Li et al. 2012). Meanwhile, our estimates of

returns to schooling are more similar to recent estimates using twin data (Li, Liu, and Zhang 2012), which find that returns to schooling are reduced to 2.7% when we eliminate the individual ability bias. When including dummies for marriage, *hukou*, and migration status, and also industry and country fixed effects in our regressions (columns 2–5), very little changes in the coefficients on education (from 4.1% in column 1 to 4.4% in column 5). This suggests that omitting these variables results in no great bias in the estimated returns to schooling. In addition, after adding firm fixed effects and individual characteristics into the regression (column 6), we find that coefficient estimates of returns to schooling decrease by 11.4% (from 4.4% in column 1 to 3.9% in column 6), which suggest that sorting effects (i.e., better-educated workers are more likely to have higher-paying jobs) are not very serious in estimating returns to schooling.

Table 3: Returns to Education for Manufacturing Workers using CEES Data
(years of schooling)

	Monthly Earnings (in log)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Years of schooling	0.041***	0.041***	0.042***	0.042***	0.044***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male (0-1 dummy)	0.242***	0.246***	0.223***	0.221***	0.223***	0.212***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.046***	0.038***	0.034***	0.034***	0.036***	0.037***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Age square/100	–0.061***	–0.052***	–0.044***	–0.044***	–0.044***	–0.043***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Married (0-1 dummy)		0.073***	0.080***	0.081***	0.086***	0.092***
		(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Rural *Hukou* (0-1 dummy)			0.001	–0.006	–0.028***	–0.062***
			(0.010)	(0.010)	(0.010)	(0.010)
Migrant worker (0-1 dummy)			0.253***	0.240***	0.132***	0.077***
			(0.009)	(0.009)	(0.011)	(0.011)
Industry dummies				Yes	Yes	
County dummies					Yes	
Firm fixed effects						Yes
Observations	7,387	7,387	7,387	7,387	7,387	7,387
R-squared	0.196	0.199	0.283	0.298	0.359	0.552

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

The figures in Table 4 confirm that better-educated workers are more likely to work less. When including only age, squared age, and a gender dummy in the regression, the estimated coefficient of years of schooling on working hours is –0.022 (column 1), which is significant at the 1% level. This means that, without considering differences in individual characteristics and workplaces, when workers receive an additional year of schooling, their working hours per month will on average decrease by 2.2%. When adding firm fixed effects and main individual characteristics into the regression, the estimated coefficient changes from –0.022 (column 1) to –0.012 (column 6), which is still significant at the 1% level. These results suggest that if workers receive an additional year of schooling, then their within-firm working hours per month will on average decrease by 1.2%. Therefore, the regressions in Table 4 show that labor market participation is distributed unevenly among workers of different education levels. Because better-educated workers are more likely to work less, only using monthly

earnings as the dependent variable will consequently underestimate the returns to schooling.

Table 4: Returns to Education for Manufacturing Workers using CEES Data
(working hours)

	Working Hours (in log)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Years of schooling	–0.022***	–0.022***	–0.018***	–0.016***	–0.015***	–0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male (0-1 dummy)	0.032***	0.032***	0.030***	0.034***	0.029***	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age	–0.006***	–0.006***	–0.005**	–0.005**	–0.005**	–0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age square/100	0.004*	0.005*	0.005*	0.006**	0.006**	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married (0-1 dummy)		0.007	0.007	0.006	0.002	–0.004
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Rural *Hukou* (0-1 dummy)			0.050***	0.044***	0.034***	0.019***
			(0.006)	(0.006)	(0.006)	(0.006)
Migrant worker (0-1 dummy)			0.026***	0.025***	0.031***	0.015**
			(0.005)	(0.006)	(0.006)	(0.007)
Industry dummies				Yes	Yes	
County dummies					Yes	
Firm fixed effects						Yes
Observations	7,253	7,253	7,253	7,253	7,253	7,253
R-squared	0.068	0.068	0.080	0.098	0.131	0.393

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Next, the regressions in Table 5 re-estimate the returns to schooling with hourly wages as the dependent variable. We find that when compared to estimates using monthly earnings as the dependent variable, the raw returns to schooling in benchmark regressions increase from 4.1% (column 1 in Table 3) to 6.3% (column 1 in Table 5). When including dummies for marriage, *hukou*, migration, and fixed effects of industries and counties in the regressions (columns 2–5 in Table 5), the estimated coefficients of education decrease by 6.3% (from 6.3% in column 1 to 5.9% in column 5). This suggests that omitting these variables does not result in serious selection bias in estimating returns to schooling. In addition, when adding firm fixed effects into the regression (column 6), the returns to schooling are reduced from 5.9% to 5.1% within firm. This suggests that about 13.6% of returns to schooling can be explained by sorting effects.

In summary, based on the CEES data, the estimated within-firm return to schooling for Chinese manufacturing workers is 3.9%~5.1%. Our estimates are significantly lower than the estimates of most prior studies (e.g., Zhang et al. 2005) but are similar to those of recent literature using twin data (e.g., Li, Liu, and Zhang 2012). Therefore, the returns to schooling for Chinese manufacturing workers are, in fact, quite a bit lower than what we can infer from existing literature.

Table 5: Returns to Education for Manufacturing Workers using CEES Data
(hourly wages)

	Hourly Wages (in log)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Years of schooling	0.063***	0.064***	0.061***	0.059***	0.059***	0.051***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male (0-1 dummy)	0.210***	0.213***	0.194***	0.188***	0.194***	0.179***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Age	0.051***	0.043***	0.038***	0.039***	0.039***	0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age square/100	–0.065***	–0.056***	–0.048***	–0.048***	–0.047***	–0.045***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Married (0-1 dummy)		0.070***	0.075***	0.078***	0.087***	0.099***
		(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Rural *Hukou* (0-1 dummy)			–0.050***	–0.052***	–0.064***	–0.083***
			(0.012)	(0.012)	(0.011)	(0.012)
Migrant worker (0-1 dummy)			0.228***	0.216***	0.102***	0.063***
			(0.010)	(0.011)	(0.012)	(0.013)
Industry dummies				Yes	Yes	
County dummies					Yes	
Firm fixed effects						Yes
Observations	7,253	7,253	7,253	7,253	7,253	7,253
R-squared	0.224	0.227	0.279	0.292	0.339	0.510

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4.2 Estimates of Returns to Different Levels of Education

To explain why the returns to schooling for Chinese manufacturing workers are so low, we add education dummies into our regression equation (2) and estimate returns to different levels of education, which are shown in Table 6. We have two findings. First, returns to academic high school are relatively lower than those for vocational high school. With individuals receiving junior high school education or below as the control group and using monthly earnings as the dependent variable, the estimated within-firm returns to academic high school is 10.2% (column 2 in Table 6), which is 4 percentage points lower than returns to vocational high school (14.2%). Similarly, when workers receive academic high school education, their within-firm working hours will decrease by 3.2% (column 4 in Table 6), 1.7 percentage points lower than those for vocational high school attendees (4.9%). This means that, when using only monthly earnings as the dependent variable, we may underestimate the gap in returns to education between academic high school and vocational high school. Next, using hourly wages as the dependent variable, the estimated within-firm return to academic high school was 13.4% (column 6 in Table 6), which is 5.8 percentage points lower than that for vocational high school (19.2%). Indeed, when considering differences between working hours, the gap in returns to education between these two groups increases from 4 to 5.8 percentage points (columns 2 and 6 in Table 6).

Second, returns to university are relatively higher than those for vocational college. Holding individuals with a high school education as the control group and using monthly earnings as our dependent variable, the estimated within-firm returns to university education is 26.3% (calculated by 0.365 minus 0.102 in column 2, Table 6), which is 10.6 percentage points higher than returns to vocational college education (15.7% as calculated by 0.259 minus 0.102 in column 2, Table 6). Furthermore, using hourly wage as the dependent variable to avoid underestimating returns to education, the estimated within-firm returns to university is 33.2% (calculated by 0.466 minus 0.134 in column 6, Table 6), which is 11.3 percentage points higher than that of vocational college (21.9% as calculated by 0.353 minus 0.134 in column 6, Table 6). Thus, considering the uneven distribution of labor market participation between different education levels, the gap in returns to education between these two groups increases from 10.6 to 11.3 percentage points (columns 2 and 6 in Table 6).

Table 6: Returns to Education for Manufacturing Workers using CEES Data
(education dummies)

	Monthly Earnings (in log)		**Working Hours** (in log)		**Hourly Wages** (in log)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
High school (0-1 dummy)	0.091***	0.102***	–0.057***	–0.032***	0.147***	0.134***
	(0.012)	(0.011)	(0.008)	(0.008)	(0.013)	(0.014)
Vocational high school (0-1 dummy)	0.119***	0.142***	–0.091***	–0.049***	0.212***	0.192***
	(0.013)	(0.013)	(0.009)	(0.009)	(0.015)	(0.016)
Vocational college (0-1 dummy)	0.234***	0.259***	–0.149***	–0.094***	0.384***	0.353***
	(0.014)	(0.014)	(0.008)	(0.009)	(0.016)	(0.017)
University (0-1 dummy)	0.398***	0.365***	–0.182***	–0.100***	0.585***	0.466***
	(0.018)	(0.018)	(0.008)	(0.010)	(0.020)	(0.021)
Male (0-1 dummy)	0.245***	0.215***	0.031***	0.032***	0.214***	0.183***
	(0.009)	(0.009)	(0.006)	(0.006)	(0.010)	(0.011)
Age	0.046***	0.036***	–0.005***	–0.003	0.051***	0.038***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Age square/100	–0.061***	–0.042***	0.004*	0.003	–0.065***	–0.044***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Married (0-1 dummy)		0.100***		–0.006		0.109***
		(0.012)		(0.008)		(0.014)
Rural *Hukou* (0-1 dummy)		–0.058***		0.016**		–0.076***
		(0.010)		(0.007)		(0.012)
Migrant worker (0-1 dummy)		0.072***		0.015**		0.057***
		(0.011)		(0.007)		(0.013)
Firm fixed effects		Yes		Yes		Yes
Observations	7,387	7,387	7,253	7,253	7,253	7,253
R-squared	0.204	0.555	0.071	0.396	0.234	0.516

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

5. HETEROGENEOUS RETURNS TO EDUCATION

In this section, we report estimates of returns to education using subsample regressions by province, gender, and migration to further explain why returns to education for Chinese manufacturing workers are so low.

First, our regressions by different groups of provinces reveal that returns to education in developed provinces are significantly higher. As shown in Table 7, with monthly earnings (hourly wages) as the dependent variable, the estimated within-firm return to schooling in Guangdong province is 4.6% (5.9%) (columns 1 and 5 in Table 7), which is 1.6 (1.9) percentage points higher than that of Hubei province (3% and 4%, respectively, columns 2 and 6 in Table 7). Furthermore, the results in Table 8 find that returns to different educational levels in Guangdong are all significantly higher than those in Hubei. For example, with monthly earnings (hourly wages) as the dependent variable, the within-firm return to high school in Guangdong is 12.1% (14.7%) (columns 1 and 5 in Table 8), which is 4.9 (3.8) percentage points higher than that in Hubei (7.2% and 10.9%, respectively, columns 2 and 6 in Table 8). Similarly, using the same method, the return to university in Guangdong reaches 31.8% (40.2%) relative to that of high school (columns 1 and 5 in Table 8), which is 11.5 (15) percentage points higher than the estimated return in Hubei (20.3% and 25.2%, respectively, columns 2 and 6 in Table 8).

In summary, our findings are different from the results of some existing literature using earlier survey data (such as Li 2003; Zhao 2002), which found that returns to schooling were even higher in less-developed regions than in developed regions. In addition, the gap in returns to schooling between developed and less-developed regions is greater than what some prior studies found (e.g., Zhang et al. 2005), which suggests that educational quality in developed regions is significantly higher than in less-developed regions.

Table 7: Subsample Regressions Estimating Returns to Education by Province
(years of schooling)

	Monthly Earnings (in log)		**Working hours** (in log)		**Hourly wages** (in log)	
	Guangdong (1)	**Hubei (2)**	**Guangdong (3)**	**Hubei (4)**	**Guangdong (5)**	**Hubei (6)**
Years of schooling	0.046***	0.030***	–0.013***	–0.010***	0.059***	0.040***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Male (0-1 dummy)	0.187***	0.245***	0.023***	0.044***	0.163***	0.201***
	(0.011)	(0.013)	(0.008)	(0.009)	(0.014)	(0.016)
Age	0.038***	0.037***	–0.004	0.000	0.042***	0.035***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.006)	(0.006)
Age square/100	–0.044***	–0.043***	0.005	–0.000	–0.048***	–0.041***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.008)	(0.008)
Married (0-1 dummy)	0.093***	0.086***	0.003	–0.014	0.093***	0.100***
	(0.015)	(0.019)	(0.010)	(0.013)	(0.019)	(0.022)
Rural *Hukou*	–0.068***	–0.055***	0.018**	0.022**	–0.086***	–0.081***
(0-1 dummy)	(0.014)	(0.014)	(0.009)	(0.010)	(0.017)	(0.017)
Migrant worker	0.078***	0.086***	0.023**	0.006	0.055***	0.081***
(0-1 dummy)	(0.016)	(0.016)	(0.010)	(0.009)	(0.019)	(0.019)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,965	3,422	3,889	3,364	3,889	3,364
R-squared	0.539	0.535	0.357	0.432	0.505	0.499

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Table 8: Subsample Regressions Estimating Returns to Education by Province
(education dummies)

	Monthly Earnings (in log)		Working Hours (in log)		Hourly Wages (in log)	
	Guangdong (1)	**Hubei (2)**	**Guangdong (3)**	**Hubei (4)**	**Guangdong (5)**	**Hubei (6)**
High school (0-1 dummy)	0.121*** (0.015)	0.072*** (0.017)	–0.025** (0.010)	–0.037*** (0.013)	0.147*** (0.018)	0.109*** (0.022)
Vocational high school (0-1 dummy)	0.148*** (0.016)	0.125*** (0.020)	–0.045*** (0.013)	–0.050*** (0.013)	0.192*** (0.021)	0.178*** (0.024)
Vocational college (0-1 dummy)	0.300*** (0.019)	0.199*** (0.021)	–0.112*** (0.012)	–0.073*** (0.013)	0.411*** (0.024)	0.273*** (0.025)
University (0-1 dummy)	0.439*** (0.024)	0.275*** (0.027)	–0.110*** (0.014)	–0.085*** (0.014)	0.549*** (0.028)	0.361*** (0.031)
Male (0-1 dummy)	0.194*** (0.012)	0.245*** (0.013)	0.021*** (0.008)	0.045*** (0.009)	0.172*** (0.014)	0.201*** (0.016)
Age	0.036*** (0.005)	0.037*** (0.005)	–0.004 (0.003)	–0.000 (0.003)	0.039*** (0.006)	0.036*** (0.006)
Age square/100	–0.042*** (0.006)	–0.044*** (0.007)	0.003 (0.004)	0.000 (0.004)	–0.045*** (0.008)	–0.041*** (0.008)
Married (0-1 dummy)	0.103*** (0.015)	0.092*** (0.019)	0.000 (0.010)	–0.014 (0.013)	0.107*** (0.018)	0.106*** (0.022)
Rural *Hukou* (0-1 dummy)	–0.061*** (0.014)	–0.051*** (0.014)	0.014 (0.009)	0.020** (0.010)	–0.076*** (0.017)	–0.074*** (0.017)
Migrant worker (0-1 dummy)	0.071*** (0.016)	0.083*** (0.016)	0.022** (0.010)	0.007 (0.009)	0.048*** (0.019)	0.077*** (0.019)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,965	3,422	3,889	3,364	3,889	3,364
R-squared	0.544	0.538	0.363	0.433	0.514	0.503

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Second, subsample regressions by gender find that returns to education for females are not robustly higher than those for males. On the one hand, with hourly wages as the dependent variable, the estimated return to schooling for females is 5% (column 6 in Table 9), which is only 0.1 percentage points higher than the estimated return for males (4.9%, column 5 in Table 9). On the other hand, as shown in Table 10, returns to high school (vocational high school) for females are significantly higher than those for males. As can be seen in column 6 of Table 10, with hourly wage as the dependent variable, the return to high school (vocational high school) for females is 16.1% (20.2%), which is 6.3 (4) percentage points higher than that for males (9.8% and 16.2%, respectively; column 5 in Table 10). In contrast to the returns to high school, returns to university (vocational college) for females are somewhat lower than those for males. As shown in column 6 of Table 10, the return to university (vocational college) relative to high school for females is 32% (18.6%), which is the same as (even 4.1 percentage points lower than) that of the male group (32% and 22.7%, respectively, column 5 in Table 10).

In summary, our findings are different from those of some existing studies, which found significantly higher returns to female education (e.g., Gustafsson and Li 2000; Li 2003; Zhang et al. 2005). We find that although returns to schooling for females are somewhat higher than for males, the returns to university education (especially vocational college education) for females are not higher. Therefore, the lower returns to education for females may help to explain the low returns to education for Chinese manufacturing workers.

Table 9: Subsample Regressions Estimating Returns to Education by Gender
(years of schooling)

	Monthly Earnings (in log)		Working Hours (in log)		Hourly Wages (in log)	
	Male (1)	**Female (2)**	**Male (3)**	**Female (4)**	**Male (5)**	**Female (6)**
Years of schooling	0.039*** (0.003)	0.036*** (0.003)	–0.010*** (0.002)	–0.013*** (0.002)	0.049*** (0.003)	0.050*** (0.004)
Age	0.041*** (0.005)	0.037*** (0.006)	0.000 (0.003)	–0.006 (0.004)	0.039*** (0.006)	0.044*** (0.007)
Age square/100	–0.049*** (0.006)	–0.042*** (0.008)	–0.000 (0.004)	0.006 (0.005)	–0.046*** (0.007)	–0.050*** (0.010)
Married (0-1 dummy)	0.149*** (0.017)	0.033* (0.019)	–0.003 (0.012)	–0.008 (0.013)	0.155*** (0.021)	0.042* (0.022)
Rural *Hukou* (0-1 dummy)	–0.062*** (0.014)	–0.045*** (0.015)	0.023** (0.009)	0.019* (0.010)	–0.088*** (0.018)	–0.065*** (0.018)
Migrant worker (0-1 dummy)	0.093*** (0.017)	0.050*** (0.018)	0.015 (0.010)	0.016 (0.011)	0.081*** (0.020)	0.034* (0.020)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,093	3,294	4,015	3,238	4,015	3,238
R-squared	0.573	0.630	0.446	0.570	0.534	0.630

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Table 10: Subsample Regressions Estimating Returns to Education by Gender
(education dummies)

	Monthly Earnings (in log)		Working Hours (in log)		Hourly Wages (in log)	
	Male (1)	**Female (2)**	**Male (3)**	**Female (4)**	**Male (5)**	**Female (6)**
High school (0-1 dummy)	0.098*** (0.017)	0.095*** (0.017)	0.004 (0.011)	–0.065*** (0.012)	0.098*** (0.021)	0.161*** (0.021)
Vocational high school (0-1 dummy)	0.145*** (0.019)	0.120*** (0.019)	–0.017 (0.014)	–0.082*** (0.015)	0.162*** (0.024)	0.202*** (0.024)
Vocational college (0-1 dummy)	0.254*** (0.021)	0.220*** (0.024)	–0.071*** (0.014)	–0.125*** (0.014)	0.325*** (0.026)	0.347*** (0.028)
University (0-1 dummy)	0.339*** (0.025)	0.381*** (0.031)	–0.079*** (0.015)	–0.097*** (0.017)	0.418*** (0.030)	0.481*** (0.034)
Age	0.040*** (0.005)	0.038*** (0.006)	0.001 (0.003)	–0.007* (0.004)	0.037*** (0.006)	0.045*** (0.007)
Age square/100	–0.048*** (0.006)	–0.044*** (0.009)	–0.001 (0.004)	0.007 (0.005)	–0.044*** (0.007)	–0.053*** (0.010)
Married (0-1 dummy)	0.154*** (0.017)	0.039** (0.019)	–0.006 (0.012)	–0.012 (0.013)	0.164*** (0.021)	0.052** (0.023)
Rural *Hukou* (0-1 dummy)	–0.056*** (0.014)	–0.046*** (0.015)	0.020** (0.009)	0.016 (0.010)	–0.080*** (0.018)	–0.062*** (0.018)
Migrant worker (0-1 dummy)	0.091*** (0.017)	0.043** (0.018)	0.016 (0.010)	0.015 (0.011)	0.077*** (0.020)	0.027 (0.021)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,093	3,294	4,015	3,238	4,015	3,238
R-squared	0.574	0.635	0.450	0.576	0.537	0.636

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Third, our between-group comparisons further find that returns to education for migrant workers are significantly higher than those for local workers. Table 11 shows that with hourly wages as the dependent variable, the estimated within-firm return to schooling for migrant workers is 6.1% (column 5 in Table 11), which is 2.2 percentage points higher than that for local workers (3.9%, column 6 in Table 11). Furthermore, the results in Table 12 show that returns to different education levels for migrant workers are all significantly higher than those for local workers. For example, as shown in column 5 of Table 12, with hourly wage as the dependent variable, the within-firm return to high school (vocational high school) for migrant workers is 15.7% (21.6%), which is 4 (5) percentage points higher than that for local workers (11.7% and 16.6%, respectively, column 6 in Table 12). Similarly, as shown in column 5 of Table 12, with hourly wages as the dependent variable, the within-firm return to university (vocational college) for migrant workers is 39% (26.3%) relative to high school, which is 14.9 (10.9) percentage points higher than that for local workers (24.1% and 15.4%, respectively, column 6 in Table 12).

In summary, our findings suggest that ability bias may be an important problem for estimating returns to education in the PRC, which is similar to Li, Liu and Zhang's (2012) findings using twin data. Without including variables to control for ability bias in regressions, the higher within-firm returns to education for migrant workers may be due to their higher ability. Therefore, if we can sufficiently control for ability characteristics, then the returns to education for Chinese manufacturing workers may become even lower.

Table 11: Subsample Regressions Estimating Returns to Education by Migration Status
(years of schooling)

	Monthly Earnings (in log)		**Working Hours** (in log)		**Hourly Wages** (in log)	
	Migrant (1)	**Local (2)**	**Migrant (3)**	**Local (4)**	**Migrant (5)**	**Local (6)**
Years of schooling	0.047***	0.030***	–0.014***	–0.009***	0.061***	0.039***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Male (0-1 dummy)	0.189***	0.228***	0.034***	0.034***	0.155***	0.194***
	(0.014)	(0.013)	(0.009)	(0.009)	(0.017)	(0.016)
Age	0.045***	0.027***	–0.003	–0.003	0.047***	0.028***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.006)	(0.006)
Age square/100	–0.053***	–0.031***	0.004	0.003	–0.055***	–0.033***
	(0.007)	(0.006)	(0.004)	(0.004)	(0.009)	(0.008)
Married (0-1 dummy)	0.103***	0.087***	0.002	–0.008	0.105***	0.097***
	(0.017)	(0.018)	(0.012)	(0.013)	(0.021)	(0.022)
Rural *Hukou* (0-1 dummy)	–0.065***	–0.061***	0.024**	0.014	–0.090***	–0.076***
	(0.016)	(0.014)	(0.011)	(0.010)	(0.020)	(0.018)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,630	3,757	3,554	3,699	3,554	3,699
R-squared	0.554	0.561	0.426	0.459	0.533	0.532

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Table 12: Subsample Regressions Estimating Returns to Education by Migration Status
(education dummies)

	Monthly Earnings (in log)		Working Hours (in log)		Hourly Wages (in log)	
	Migrant (1)	**Local (2)**	**Migrant (3)**	**Local (4)**	**Migrant (5)**	**Local (6)**
High school (0-1 dummy)	0.112*** (0.018)	0.095*** (0.016)	–0.043*** (0.012)	–0.021* (0.012)	0.157*** (0.022)	0.117*** (0.020)
Vocational high school (0-1 dummy)	0.163*** (0.020)	0.122*** (0.019)	–0.054*** (0.015)	–0.038*** (0.013)	0.216*** (0.025)	0.166*** (0.022)
Vocational college (0-1 dummy)	0.311*** (0.023)	0.199*** (0.021)	–0.111*** (0.014)	–0.070*** (0.014)	0.420*** (0.028)	0.271*** (0.025)
University (0-1 dummy)	0.428*** (0.026)	0.270*** (0.029)	–0.120*** (0.016)	–0.080*** (0.015)	0.547*** (0.031)	0.358*** (0.033)
Male (0-1 dummy)	0.195*** (0.014)	0.229*** (0.013)	0.033*** (0.009)	0.033*** (0.009)	0.162*** (0.016)	0.195*** (0.016)
Age	0.041*** (0.005)	0.028*** (0.005)	–0.002 (0.003)	–0.003 (0.003)	0.042*** (0.006)	0.030*** (0.006)
Age square/100	–0.049*** (0.007)	–0.032*** (0.006)	0.002 (0.004)	0.004 (0.004)	–0.049*** (0.009)	–0.034*** (0.008)
Married (0-1 dummy)	0.115*** (0.017)	0.090*** (0.018)	–0.001 (0.012)	–0.010 (0.013)	0.121*** (0.021)	0.102*** (0.022)
Rural *Hukou* (0-1 dummy)	–0.057*** (0.016)	–0.060*** (0.014)	0.021* (0.011)	0.012 (0.010)	–0.079*** (0.020)	–0.072*** (0.018)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,630	3,757	3,554	3,699	3,554	3,699
R-squared	0.559	0.562	0.429	0.461	0.539	0.534

Notes: the numbers in brackets are robust standard errors. *, ** and *** represent the significance at 10%, 5%, and 1% levels, respectively.

6. CONCLUSION

Using data from the CEES, which is a new dataset collected by the authors, our paper first estimates returns to education for Chinese manufacturing workers. Our estimate finds that returns to education for Chinese manufacturing workers are significantly lower than those presented in existing literature (Zhang et al. 2005; Li et al. 2012; Li, Liang, and Wu 2016). Factoring firm fixed effects into our regressions, with monthly earnings (hourly wages) as the dependent variable, the estimated within-firm return to schooling is 3.9% (5.1%), which is also significantly lower than the estimates (close to 10%) of most prior studies using Chinese or Asian data (e.g., Heckman and Li 2004; Zhang et al. 2005; Li et al. 2012). Our estimates of returns to schooling are closer to recent estimates using twin data (Li, Liu, and Zhang 2012), which find that returns to schooling are reduced to 2.7% using within-twin fixed effects to sufficiently control for individual ability bias.

To explain why the returns to education have been so low for Chinese manufacturing workers in recent years, we add education dummies into our regressions and further estimate returns to different levels of education. First, we find that returns to academic high school (vocational college) are lower than those for vocational high school (university). Using hourly wages as the dependent variable, the estimated within-firm return to academic high school is 13.4%, which is 5.8 percentage points lower than that for vocational high school (19.2%). The low return to high school may be due to the Chinese education system's single-minded focus on examination preparation at the high school level because the material in these examinations often bears little relation to the

knowledge and skills required for work (Han and Yang 2001; Zhang 2009; Li, Liu, and Zhang 2012).

Second, using hourly wages as the dependent variable, relative to the return to high school, the estimated within-firm return to vocational college is 21.9%, which is 11.3 percentage points lower than that for university education (33.2%). The low return to vocational college may be attributable to inequality of educational resources. The Chinese government allocates a disproportionate amount funding and highly-skilled teachers toward university education, while vocational colleges remain under-served.

Our between-group comparisons further explain the low returns to education in the PRC. On the one hand, the returns to schooling in less-developed regions are significantly lower than in more-developed regions, which suggesting that the quality of education in these regions is poor. Due to the PRC's growth-focused government and decentralized fiscal system (Li and Zhou 2005; Chen, Li, and Zhou 2005; Jin, Qian, and Weingast 2005), local officials in less-developed regions often have fewer incentives and capabilities to make long-term investments in education (Wong 1997; Huang, Rozelle, and Wang 2006).

In contrast to most existing studies (e.g., Gustafsson and Li 2000; Li 2003; Zhang et al. 2005), our estimated returns to education for females are not significantly higher than those for males. This fall in returns to education for females may help lead to low overall returns to education for Chinese manufacturing workers.

Finally, we find that within-firm returns to schooling for migrant workers are significantly higher than those for local workers. When we exclude variables controlling for ability bias in our regressions, our results show that ability bias may result in an overestimated value for returns to education in the PRC (Li, Liu, and Zhang 2012). Consequently, after sufficiently controlling for ability characteristics, the true returns to education for Chinese manufacturing workers may become even lower.

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APPENDIX

Table A1: Sample Size and Response Rates of the CEES Survey in Hubei and Guangdong Provinces of the People's Republic of China

	Number of Observations	Response Rate
Firm survey 2015 (Guangdong only)	573	82%
Firm survey 2016	1,122	85%
New sample (Hubei)	585	83%
Follow up sample (Guangdong)	487	85%
New sample (Guangdong)	50	--
Worker survey 2015 (Guangdong only)	4,838	88%
Worker survey 2016	9,103	80%
New sample (Hubei)	4,114	89%
Follow up sample (Guangdong)	2,575	53%
New sample (Guangdong)	2,414	94%

Table A2: Summary Statistics of the Individual Characteristics of CEES

	All Firms		Guangdong		Hubei	
	Obs.	Mean (Std.)	Obs.	Mean (Std.)	Obs.	Mean (Std.)
Male (0-1 dummy)	8,931	0.56 (0.50)	4,895	0.54 (0.50)	4,036	0.58 (0.49)
Age	8,848	36 (9.5)	4,834	34 (8.8)	4,014	38 (9.9)
Married (0-1 dummy)	8,686	0.80 (0.40)	4,659	0.76 (0.43)	4,027	0.85 (0.36)
Rural *hukou* (0-1 dummy)	8,652	0.59 (0.49)	4,642	0.69 (0.46)	4,010	0.48 (0.50)
Migrant (0-1 dummy)	10,646	0.53 (0.50)	6,646	0.70 (0.46)	4,000	0.26 (0.44)

Notes: statistical analyses are based on the "China Employer-Employee Survey" (CEES) data.