

## **SPECIAL ISSUE: URBANIZATION AND EMPLOYMENT OF MIGRANT WORKERS IN CHINA**

### **Factors Influencing Migrant Workers' Employment and Earnings —The Role of Education and Training<sup>1</sup>**

Wang Dewen,<sup>a</sup> Cai Fang<sup>b</sup> and Zhang Guoqing<sup>c</sup>

<sup>a</sup> *Institute of Population and Labor Economics, Chinese Academy of Social Sciences*

<sup>b</sup> *Institute of Population and Labor Economics, Chinese Academy of Social Sciences*

<sup>c</sup> *International Labor Organization Office for China and Mongolia*

在城市劳动力市场上，农村劳动力根据个人的人力资本积累状况和当地的劳动力市场条件，在成为自我经营者和工资收入者之间进行就业选择。简单的Mincer工资方程回归结果显示，工资收入者比自我经营者的教育回报率高出2个百分点左右。在矫正了样本选择偏差之后，拓展的Mincer工资方程对工资收入者的教育回报率估计结果在5.3%-6.8%之间。从培训角度看，简单培训、短期培训和正规培训对农民工再流动都有显著作用，但简单培训对农民工的工资收入作用不显著，而短期培训和正规培训则对其工资收入有着重要的决定作用。此外，工资拖欠等权益保护问题也对农村劳动力再流动有重要影响。在处理农民工的个人异质性和教育内生性问题时，本文还发现父母受教育年限不是一个理想工具变量。

关键词：农民工 就业选择 再流动 教育与培训的回报率 处理效应模型

In the urban labor market, the rural labor force can choose whether to become self-employed or work for wages depending on their stock of human capital and local labor market conditions. A simple Mincer earnings regression shows that the rate of return to schooling for wage earners is two percentage points higher than that for the self-employed. After correcting for bias in sample selection, the expanded Mincer earnings equation estimated the rate of return to schooling for wage earners at between 5.3 and 6.8 percent. From the standpoint of training, we found that the simplest form of training, short-term training and formal training played an important role in promoting migrant workers' repeat mobility. However, the simplest form of training did not have a significant effect on earnings,

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whereas short-term and formal training played an important determining role in this respect. Moreover, rights protection issues such as wage arrears also had an important effect on migrant workers' repeat mobility. In handling heterogeneity and endogenous educational variables among migrant workers, the authors found that the years of schooling of the parents of migrant workers were not an ideal instrumental variable.

**Keywords:** migrant workers, employment choices, repeat mobility, rate of return to education and training, treatment effects model

## I. Prologue

The massive flow of rural labor to urban areas has been an important force in promoting the development of China's labor market since reform and opening up in 1978. Statistics show that the outflow of labor from the rural areas increased from 114 million in 2003 to 132 million in 2006.<sup>2</sup> This massive flow of population has had a positive effect on China's economic structural adjustment and urban development, gradually creating conditions for the reformation of China's household registration (*hukou*) system and the maturation of labor market. The post-1978 policy on rural labor migration moved from permitting to encouraging such migration, heralding a completely new era for China's rural labor migration.

Guided by the market and with wages as a signaling mechanism, rural workers found employment through the supply and demand mechanism in the labor market. Studies show that these migrant workers tend to be young or in the prime of life and relatively well educated, with more men than women.<sup>3</sup> These distinctive features are the result of labor market mechanisms. From the perspective of market demand, migrant workers' age and years of schooling are generally connected with productivity. Women confront the problem of a falling participation rate in non-agricultural employment once they are of the age for marriage and child-bearing. Thus the match between labor market supply and demand results in a greater proportion of males and people with higher human capital shifting to urban areas and the non-agricultural sector.

The higher return to schooling in the cities is another important incentive in rural migration into urban areas. In the early years of China's reform and opening up, the rate of return to schooling averaged around 3.3 percent, and was higher in the countryside than in the cities.<sup>4</sup>

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2 National Bureau of Statistics of China, "Numbers, Structure and Characteristics of Migrant Workers Working in Cities in 2004"; "Number of Migrant Workers Working Away from Home Continued to Increase in 2006."

3 National Bureau of Statistics of China, "Numbers, Structure and Characteristics of Migrant Workers Working in Cities in 2004."

4 E. N. Johnson and G. Chow, "Rates of Return to Schooling in China," pp.101–113. Byron and Manuloto (in "Returns to Education in China"), and Maurer-Fazio (in "Earnings and Education in China's Transition to a Market Economy") argue that the rates of return to schooling in urban areas were even lower, at an estimated 1.4 percent to 2.9 percent.

However, with the market-oriented reform of employment from the 1990s on, the rate of return to schooling in urban areas witnessed a steady increase from 6.8 percent in 1991 to 8.5 percent in 2000,<sup>5</sup> or from 4.0 percent in 1988 to 10.2 percent in 2001,<sup>6</sup> close to the average level of developing countries.<sup>7</sup> By contrast, the return to schooling in the countryside remained on the low side. Examining data collected from China's township and village enterprises (TVEs) in 1998, Ho *et al.*<sup>8</sup> estimated that the return to schooling in the countryside was between 3.2 and 5.4 percent. The evident discrepancy between the countryside and the cities gave added impetus to the growing exodus of rural labor. Using rural household data for 2000, de Brauw and Rozelle<sup>9</sup> found that the return to schooling among the migrant rural labor force averaged around 6.4 percent, higher than the rate of return in the rural labor market.

A considerable amount of the literature on rural labor mobility analyzes the rate of return to schooling. Due to the limited availability of data, few studies have analyzed education and training as determinants of migrant workers' employment choices and earnings. This paper will attempt to examine this relationship. The remainder of the paper is organized as follows. The second section proposes an analytical framework for dealing with China's rural labor mobility; the third provides a brief introduction and description of the statistical sources; the fourth discusses the issue of migrant workers' employment choices and repeat mobility; the fifth examines the issue of migrant workers' wage determination and the sixth uses the treatment effects model to estimate the average return to training. The last part provides the conclusion and offers some policy suggestions.

## II. An Analytical Framework

In the course of industrialization and urbanization, the flow of rural labor to the cities is generally one-way; after migrating to the city, people do not return to the countryside. Even if "circular migration" occurs, it affects a small proportion of migrants. Industrialization is accompanied by increasing urbanization, with corresponding changes in the economic and employment structure leading to a decreasing share of agriculture in GDP and of agricultural employment. This process of development is borne out by the experience of developed and newly industrialized countries and regions around the world.

Due to the existence of the household registration system, China's urbanization and industrialization have not kept pace with one another. In 2006, the share of agriculture in GDP

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5 Chen Xiaoyu, Chen Liangkun and Xia Chen, "Evolution and Implications of Returns to Schooling in China's Urban Areas in the 1990s," pp. 65-72.

6 Zhang Junsen *et al.*, "Economic Returns to Schooling in Urban China: 1988-2001."

7 George Psacharopoulos, "Returns to Education: A Global Update," pp. 1325-1344.

8 Samuel Ho *et al.*, "Privatization and Enterprise Wage Structures during Transition: Evidence from China's Rural Industries," pp. 659-688.

9 Alan de Brauw and Scott Rozelle, "Reconciling the Returns to Education in Off-farm Wage Employment in Rural China."

fell to 11.7 percent while employment in the agricultural sector remained at 42.6 percent. Under the household registration system, almost all the flow of labor from the countryside to the cities follows a pattern of “circular migration” with the year as unit. Very few migrants can break through the constraints of the household registration system and become urban residents permanently domiciled in the city. In the course of circular migration, the rural labor force flocking to the cities face multiple choices, such as whether to leave home, what kind of work to look for once they leave, whether to return to the city after going home for the Spring Festival, etc. Such circular migration confronts rural people with constant decisions about whether to “go” or to “stay.”

The classic model of migration generally divides the urban economy into two sectors, the formal and the informal, corresponding to the formal and informal labor market. Some studies show that in developing countries, rural labor is concentrated in the informal sector, where migrants hope to earn a subsistence living through self-employment while they wait for better paid job opportunities in the formal sector. Since this sector has limited job creation capacity, increased migration means a rise in the number and proportion of job-seeking migrants in the informal sector, leading to serious unemployment and job shortages.<sup>10</sup> By contrast, although a relatively high proportion of China’s migrant labor force is employed in the informal sector in the cities, their unemployment rate is low.<sup>11</sup> The survey *China’s Urban Employment and Social Security* also shows that their extended working hours enable the self-employed to gain a higher monthly income than wage-earners.

Ranis and Stewart<sup>12</sup> conducted further research into the informal sector in developing countries. They argued that if one divides the informal sector into three components: a dynamic non-traditional component, a component providing services for the formal sector and a static traditional component, then even if the job-creating ability of the formal sector is low, the first two components of the informal sector can create plentiful job opportunities for the rural labor force. Overall, the facts of the development of China’s urban labor market conform to this pattern. Although the self-employed are generally placed in the informal category, they may belong to its dynamic non-traditional component or the component providing services for the formal sector. Therefore, analyzing the employment choices and wage determination of the rural labor force is of particular importance to our understanding of the evolution of China’s urban labor market.

In the dual economy migration model of rural workers’ job-seeking behavior, migration decisions are determined by a comparison between workers’ reservation wage and their

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10 J. Harris and M. Todaro, “Migration, Unemployment and Development: A Two Sector Analysis,” pp. 126-142; G.S. Fields, “Rural-Urban Migration, Urban Unemployment and Underemployment, and Job-Search Activity in LDCs,” pp. 165-187.

11 Wang Dewen, Cai Fang and Wu Yaowu, “Migration, Unemployment and the Segmentation of Urban Labor Markets—Why Is the Unemployment Rate Low among Migrant Workers?”

12 G. Ranis and F. Stewart, “V-Goods and the Role of the Urban Informal Sector in Development,” pp. 259-288.

expected income in different urban sectors. If their expected urban income is lower than their reservation wage, they will stay in the countryside and continue to pursue agricultural activities. Should their expected urban income be higher, they will choose to migrate to urban areas. Once they decide on migration and move to the cities, they have to decide whether to become a wage earner or be self-employed. Which type of work they end up choosing is largely determined by their individual endowments (years of schooling, managerial ability, etc.), as well as labor market conditions (high or low unemployment, institutional and policy constraints, etc.).

From the individual's perspective, urban labor market conditions are a given. If becoming a wage earner gives a higher rate of return to schooling, then the rural labor force will seek a job that pays wages. Conversely, if being self-employed gives a higher rate of return, they will choose to become self-employed. Thus it can be seen that individual accumulation of human capital plays an important role in employment choices and wage determination. Similarly, the household registration system dictates that migrant workers adopt a "circular migration" policy with the year as unit. Decisions on whether to go the city the following year are largely dependent on a comparison between the opportunity costs connected with migration and the expected benefits. If the latter are low or involve risks such as wage arrears and so on, the likelihood of going to the city falls sharply. However, the human capital formed from education and training and their returns are also important variables in decisions on repeat migration.

### III. Data Sources and Description

The data in this paper come from two sources. The first is the questionnaire survey "Urban Employment and Social Security in China," conducted by the Institute of Population and Labor Economics of the Chinese Academy of Social Sciences in twelve Chinese cities in 2005. The survey sampled 5,520 rural households (12,820 people) using stratified random equidistant sampling. Having excluded 24.3 percent of who were not from the countryside, we obtained 4,179 households (9,954 people). The survey collected information on demographic characteristics (age, sex, years of schooling, marital status, political affiliation, etc.) and employment status (employment history, type of employment, industry, occupation, earnings, etc.), as well as parents' years of schooling and other information on family background. Using information on family background as an instrumental variable should help us analyze the endogenous nature of education.

According to *Urban Employment and Social Security in China*, an extremely high proportion of rural migrant labor is self-employed, averaging nearly 60 percent in the twelve sampled cities.<sup>13</sup> (See Table 1). On a city basis, leaving out Wuxi, Zhuhai and Shenzhen, the

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13 A survey conducted by the National Bureau of Statistics of China in 2006 showed that the proportion of migrant workers employed in the manufacturing and construction industries was 35.7 percent and 20.5 percent respectively. However, as community records were used for the sampling frame, it was easy to omit migrant workers employed in these industries in the course of sampling, thus inflating the proportion of the self-employed.

proportion of the self-employed was well above 50 percent of the total number of migrant workers, and in Wuhan, Xi'an and Baoji it exceeded 70 percent. In five provincial capitals, the self-employed averaged 69.3 percent of the total number of migrant workers, about 22.1 percentage points higher than in five medium-sized surrounding cities. In terms of monthly earnings, the average monthly income of the self-employed in the five capital cities was 1.13 times that of wage-earners; in the five medium-sized surrounding cities, it was 1.29 times that of wage-earners. As the self-employed normally work extended hours, we adjusted wages to take account of working hours. After the adjustment, the hourly earnings of the self-employed in the five capital cities were about 82 percent of those of wage earners while in the five medium-sized cities, they were 17 percent higher than those of wage earners (see Table 1).

The second source of data is the *Survey of Migrant Workers' Employment* conducted by the Ministry of Labor and Social Security (MLSS) in the spring of 2006 and 2007. This dedicated survey was conducted each year just before the Spring Festival, starting from 2006. It is targeted on migrant workers returning from cities to their hometowns for the Spring Festival in some "model migrant worker departure counties." Sampling points were generally located at long-distance coach stations, railway stations, etc. In each county, at least a hundred people were sampled. The sample content was quite simple: the main information collected was respondents' sex, age, years of schooling, training, wages, place and industry of employment, whether they were owed wages and whether they intended to work outside their hometown in the coming year. Since migrant workers who failed to return to their hometowns for Spring Festival could not be included, some sampling errors were inevitable. The survey conducted in spring 2006 covered 48 counties in 25 provinces and sampled 5,300 migrant workers, and the one conducted in spring 2007 covered 46 counties in 25 provinces and sampled 5,130 migrant workers, in both cases collecting basic information.

From the point of view of econometrics, it is generally necessary to use hourly earnings data to study the impact of education and training on the employment and income of migrant workers. The survey *Urban Employment and Social Security in China* can provide such data for analysis of the returns to schooling, but that dataset has very little information on training; training takes up only 3.7 percent of the total, rendering the data unsuited to econometric analysis. By contrast, the *Survey of Migrant Workers' Employment* effectively remedies this deficiency. According to the two surveys administered by the MLSS (see Table 2), in 2005, about 24.6 percent of migrant workers attended the simplest form of training of less than fifteen days, while 18.9 percent took part in short-term training of fifteen to ninety days' duration and 13.7 percent took part in formal training of more than ninety days' duration. Altogether, about 57.2 percent of migrant workers took part in training of some sort. In 2006, 21.5 percent took part in the simplest form of training, 20.2 percent took part in short-term training and 13.1 percent took part in formal training. Since the simple form of training only consisted of guidance, it did not contribute substantially to skill formation. If we take short-term and formal training together, the MLSS survey data approximates to the findings of

the National Bureau of Statistics of China. According to the latter, the proportion of migrant workers receiving training was 34.4 percent and 35.2 percent in 2005 and 2006 respectively.<sup>14</sup>

The complementary nature of the two datasets can be seen from the following. (1) The data in *Urban Employment and Social Security in China* can be used to study migrant workers' employment choices and returns to education, but is unsuitable for studying returns to training. (2) The *Survey of Migrant Workers' Employment* can be used to study the impact of education and training on migrant workers' repeat migration as well as the returns to training, but is not suited to analysis of the returns to education. To facilitate a comparison with estimates in the relevant literature, we have selected a wage equation for migrant workers who have had a long period of urban employment to estimate the rates of return to education and training for migrant workers.

#### IV. Migrant Workers' Employment Choices and Repeat Migration

Using the survey data in *Urban Employment and Social Security in China*, this paper calculates the marginal effects on migrant workers' employment choices of individual variables (sex, marital status, years of schooling, work experience, experience squared, political affiliation, number of friends acquired by relatives who had moved to the city, family size, etc.) and labor market conditions (urban dummy variable). For given individual variables ( $X$ ) and the labor market conditions variable ( $D$ ), the probability of a migrant worker's becoming a wage earner ( $Z=1$ ) is:  $P_i(Z=1|X, D) = \text{Pr } ob(X\beta + \gamma D + \varepsilon > 0)$ . In this equation,  $\beta$  and  $\gamma$  are the marginal effects after controlling for other variables and  $\varepsilon$  is a stochastic disturbance term. For the results of the regression of the marginal effects probability selection model, see Table 3.

In the first regression equation, only the marriage variable involving divorce/loss of spouse and experience squared were not statistically significant. In the second regression equation, we incorporated the social capital indicators of political affiliation and social network to observe whether they affected choice behavior. Neither was statistically significant. From the findings of the second regression equation, we drew the following conclusions:

First, male migrant workers are more likely to choose to become wage earners than are females. After controlling for other variables, the marginal probability of male migrant workers' becoming wage earners is 13.8 percent higher than that of female migrant workers.

Second, marital status and family size have a significant influence on migrant workers' employment choices. After controlling other variables, we found that being married, divorced or widowed lowers the probability of becoming a wage earner by 14.8 to 18.6 percent. Increased family size lowers the probability of becoming a wage-earner by 6.2 percent. This

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14 National Bureau of Statistics of China, "The Number of Migrant Workers Continued to Increase in 2005"; "Number of Migrant Workers Working Away from Home Continued to Increase in 2006."

finding may show that family decision-making has to take into account both income creation and taking care of other family members.

Third, education and training can significantly increase the probability of becoming a wage earner. After controlling other variables, we found that each additional year of schooling increased the probability of becoming a wage earner by 1.1 percent. Receipt of training increased the probability of becoming a wage earner by 13.2 percent.

Fourth, the marginal effect of the experience variable is evident in the fact that as age increases, the likelihood of becoming a wage earner first decreases and then increases.

Finally, we found that individuals' political affiliations and social networks in the city were not statistically significant.

According to the MLSS survey, 74.6 percent and 75.6 percent of migrant workers in 2006 and 2007 respectively said they would continue to leave home to work in the city. To calculate the marginal effect of different variables on migrant workers' repeat migration, we coded "leaving home" as "1" and "other" as "0." For the result of the regression equation obtained by using the dprobit model, see Table 4. Table 4 suggests that the regression coefficients of the sex, education and training, and wage arrears variables were significant at the 1 percent or 5 percent level while the regression coefficients of the variables of experience and experience squared were statistically insignificant.

In terms of education and training, after controlling other variables, each additional year of schooling was found to raise the probability of choosing to work away from home by 0.7 percent. The marginal effect of short term training was the highest, at 11.2 percent. Receiving the simplest form of training increased the probability of repeat migration by 8.5 percent, while formal training raised this probability by 8.4 percent. It can be seen that irrespective of duration, training significantly increases the probability of repeat migration.

Arrears in wages act as a disincentive to repeat migration. According to the MLSS survey, 19.6 percent of migrant workers were owed unpaid wages in 2006. There was some improvement in 2007, when the problem affected 18.7 percent of migrant workers. After controlling other variables, it was found that the probability of repeat migration fell by 12.6 percent for migrant workers who were owed small amounts of wages. However, for those owed a large amount or all of their wages, the probability of repeat migration fell by 22 percent and 27 percent respectively. It can be seen that a realistic solution to migrant workers' arrears of wages and protection of their legitimate rights and interests would provide a strong impetus to their repeat migration.

## **V. Years of Schooling and Wage Determination**

Human capital theory posits that differences in individual earnings derive from differences in human capital investment and accumulation. Empirical interpretations generally adopt the

Mincer wage equation<sup>15</sup> to estimate returns to schooling, observe labor market changes and discuss human capital as a determinant of income and wages. The Mincer wage equation is an empirical equation. Its semi-log function takes the following form:

$$\ln(Y_i) = \ln(Y_{0i}) + rS_i + \beta_1 E_i + \beta_2 E_i^2 + \varepsilon_i$$

In this equation,  $Y_i$  represents earnings (hourly wage),  $Y_{0i}$  represents initial or subsistence earnings,  $S_i$  represents years of schooling,  $E_i$  represents experience,  $E_i^2$  represents experience squared and  $\varepsilon_i$  represents error.

Using the Mincer wage equation to estimate returns to schooling raises two important issues. One is the heterogeneity of individual ability, that is, the issue of “ability bias.”<sup>16</sup> If the regression equation fails to take this heterogeneity into consideration, the estimation of returns to schooling will be biased. Assuming that the above equation should incorporate a variable indicating individual ability  $A_i$ , the true equation function should take the form of:

$$\ln(Y_i) = \ln(Y_{0i}) + rS_i + \beta_1 E_i + \beta_2 E_i^2 + \beta_3 A_i + \varepsilon_i$$

If the ability variable is missing, then the estimated rate of return to schooling should be  $p \lim \hat{r} = r + \beta_3 \frac{Cov(S_i, A_i)}{Var(S_i)}$ . If we assume a positive relationship between individual ability and education, empirical analysis may lead to an overestimation of the rate of return to schooling. To deal with this kind of problem in practice, researchers normally choose to incorporate more control variables, such as IQ scores, aptitude scores and family background variables.

Another issue in estimation of the rate of return to schooling involves the endogeneity of schooling.<sup>17</sup> At present, economics is attempting to use quasi-natural experiments to resolve this problem. The regression technique commonly uses family background etc. as instrumental variables to handle the issue of the endogeneity of schooling. Whether family background is indeed an appropriate instrumental variable has been the subject of much controversy in econometrics. Card<sup>18</sup> argues if family background fails to have a direct effect on wage income decisions or to reflect the effect of the absent ability variable, it is not an ideal instrumental variable. However, Connelly and Uusitalo,<sup>19</sup> using a simulation study of Finnish data, found that using family background variable as an instrumental variable rejected the hypothesis that it was unrelated to the residuals in the wage equation.

The economic mechanism behind the effect of family background on returns to schooling

15 J. Mincer, *Schooling, Experience and Earning*.

16 Zvi Griliches, “Estimating Returns to Schooling: Some Econometric Problems,” pp. 1-22.

17 P. Carneiro, J.J. Heckman and E. Vytlacil, “Understanding What Instrumental Variables Estimate: Estimating Marginal and Average Returns to Education”; James J. Heckman, Lance J. Lochner and Petra E. Todd, “Fifty Years of Mincer Earnings Regressions.”

18 D. Card, “The Causal Effect of Education on Earnings.”

19 Karen Connelly and Roope Uusitalo, “Estimating Heterogeneous Treatment Effects in the Becker Schooling Model.”

is quite complex. Altonji and Dunn<sup>20</sup> argue that parental education affects not only their children's school learning but also the quality of the children's pre-school education. These differences would be reflected in their adult performance in the labor market. San-Segundo and Valiente<sup>21</sup> stress that the relationship between family background and returns to schooling reflects a social and economic structure. In such a structure, family and social influence play an important role in perpetuating intergenerational inequality. If wealthy and well-educated parents can provide their children with more and better learning opportunities, then family background will affect their children's educational attainment.<sup>22</sup> For this reason, Schultz<sup>23</sup> has pointed out that family background can serve as a proxy variable for unobserved variables such as individual ability and educational quality.

Some studies show that family background has a significant positive effect on returns to schooling. In studying the wage equation for males, Heckman and Hotz<sup>24</sup> found that incorporation of variables for mother's and father's education did indeed have a positive effect on their children's earnings, with the effect of maternal education being especially great. When parental education was incorporated into the regression equation, the rate of return to schooling in the male wage equation fell by 25 percent. De Brauw and Rozelle's research on rural households also found that parental education had a positive effect on children's earnings in the non-agricultural sector.<sup>25</sup>

Our empirical analysis adopts three methods of handling the Mincer equation. First, we calculate a simple Mincer equation. Second, we introduce sex, marital status, political affiliation, training, parental years of schooling and other variables and conduct a regression estimation on the expanded Mincer equation. The main reason for this approach was to deal with the problem of individual heterogeneity discussed in this section. Third, we use parental years of schooling and the locus of the individual's primary schooling as instrumental variables to deal with the problem of the endogeneity of schooling.

In the treatment of variables, experience is age minus years of schooling and minus a further six years. Experience squared is used to control the non-linear relationship between earnings or wages and experience. Political affiliation is incorporated into the wage equation to examine the effects of political capital on wage determination. Training is incorporated to examine the effect of training on migrant workers' wage determination.

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20 J. Altonji and Thomas A. Dunn, "The Effects of Family Characteristics on the Returns to Education," pp. 692-705.

21 Maria J. San-Segundo and Asuncion Valiente, "Family Background and Returns to Schooling in Spain."

22 Yao Xianguo, Huang Zhiling and Su Zhenhua, "Family Background and Rates of Return to Education."

23 T. Schultz, "Education Investments and Returns."

24 J. Heckman and J. Hotz, "An Investigation of the Labor Market Earnings of Panamanian Males: Evaluating the Sources of Inequality," pp. 507-542.

25 Alan de Brauw and Scott Rozelle, "Reconciling the Returns to Education in Off-farm Wage Employment in Rural China."

Table 5 reports the findings of our regression estimation of the wage equation for migrant workers, based on survey data from *Urban Employment and Social Security in China*. This table presents separate wage equations for the self-employed, wage earners and all migrant workers. We first used a simple Mincer equation to carry out the regression estimation, then an expanded Mincer equation. Finally, we used instrumental variables to calculate the Mincer equation. Therefore, regression equations 1, 2, 4, 5, 7 and 8 in Table 5 are robust estimation findings using the OLS method. Regression equations 3, 6 and 9 used the instrumental variable method.

In the findings of the simple Mincer earnings equation, all of the  $\beta$  coefficients of the explanatory variables were statistically significant with  $p$ -value at below the .01 level. Furthermore, the direction was also consistent with our theoretical expectations. In the regression equation for the self-employed, the rate of return to schooling was 4.7 percent; for wage earners, it was 6.8 percent; and for all migrant workers, it was 5.6 percent. It can be seen that if we do not distinguish between different types of employment, the regression results will lead to an underestimation of the rate of return to schooling for wage earners.

In the expanded Mincer earnings equation, the regression coefficients of training variable and father's years of education appeared statistically insignificant across all equations. The regression coefficient of marital status was significant in Equation (6), with the  $p$ -value being below the .01 level, but was not significant in Equations (3) and (9) in all equations. Sex was significant in all equations, with the  $p$ -value being below the .01 level. Mother's years of schooling was significant in Equations (3) and (9) but not in Equation (6). Since there is a certain linear relationship between experience and experience squared and the introduction of new variables, this variable was not significant in Equation (5).

As noted earlier, the introduction of new variables as a way of treating ability or missing variables resulted in a fall in returns to schooling across all categories. Compared with the simple Mincer earnings equation, the rates of return to schooling among the self-employed and wage earners in the expanded Mincer regression equation decreased by 2.1 percentage points while the return to schooling for migrant workers as a whole decreased by 2.2 percentage points.

In the expanded Mincer earnings equation, taking the years of schooling of both parents as the family background variable had different effects on the two different types of employment (i.e. the self-employed vs. wage earners). For the former, mother's years of schooling had a statistically significant effect on individual earnings, whereas for the latter, parents' years of schooling was not significant. This finding is very interesting. Parents' years of schooling as a family background variable may imply a gift for business management passed down in the family or related to the individual's natural endowments. However, these abilities conferred no advantage on the attainment of wage income in the labor market.<sup>26</sup>

26 If parent's years of schooling are inserted separately into the expanded Mincer equation, both are significant in the regression equation for the self-employed. However, the marginal effects associated with mother's years of schooling are greater than those of father's years of schooling. However, in the equation for wage earners, neither is significant.

In terms of the instrumental variables regression findings, parents' years of schooling was shown not to be a good variable for handling the question of endogeneity of migrant workers' education, particularly when used to calculate the regression equation for wage earners. With the addition of the instrumental variables, the return to schooling for the self-employed rose to 7.8 percent but that for wage earners was negative and statistically insignificant.<sup>27</sup>

In using material on wage earners to predict the rate of return to schooling, sample selection should be considered. Table 6 presents estimates based on Heckman selection equation.<sup>28</sup> In the simple Mincer earnings equation, the inverse Mills ratio is at the .01 or the .05 significance level. In the new calculation, the return to schooling is between 5.3 percent and 6.8 percent. This is consistent with the rates of return to schooling presented in Table 6, but 0.6 percent higher than those obtained after correcting the sample selection bias in the extended Mincer earnings equation in Table 8 (5.3 percent).

## VI. The Average Treatment Effects and Rate of Return to Training

In recent years, the employment policy environment for rural migrant workers has undergone a fundamental change. Under the guidance of the idea of "equal treatment," governments have introduced a series of policy measures including greater efforts in training migrant workers, improving the level of public services they enjoy and gradually bringing them into the urban social security system. For instance, in September 2003, the General Office of the State Council released a *Training Program for Migrant Workers between 2003 and 2010* formulated by six ministries under the State Council. The program planned for the delivery of pre-employment introductory training in 2003–2005 for ten million migrant workers, of whom five million would receive occupational skills training. Another fifty million migrant workers who were already employed in the non-agricultural sector would receive workplace training. From 2006 to 2010, fifty million migrant workers would receive pre-employment introductory training, of whom thirty million would also receive occupational skills training. On March 26, 2006, the State Council released the document *Some Views on Solving the Problems of Migrant Workers*, which gives an important role to strengthening employment services and training for migrant workers.

With the implementation of government training programs and policies, training opportunities and channels for migrant workers have expanded substantially. The implementation of these training programs and policies somewhat resembles a quasi-natural experiment. In the course of implementing the programs, some migrant workers participated in training while others did not. We can thus divide migrant workers into two groups: the

27 If parents' years of schooling is used alone as an instrumental variable, even though the rate of return for wage earners is 3.6 percent, it is not statistically significant. In these circumstances, the rate of return for the self-employed is 52.2 percent.

28 J. Heckman, "Sample Selection Bias as a Specification Error," pp. 153–161.

group that received training and the group that did not. If the training was mandatory and the question of choice did not enter into it, we could make an estimation using the dummy variable method. However, if personal choice was involved in the decision to participate in training, it would be necessary to use the average treatment effects model to estimate the rate of return to training. Otherwise, the problem of biased estimation would arise.

The form of the average treatment effects equation is generally set as follows:<sup>29</sup>

$$y_j = X_j\beta + \delta z_j + \varepsilon_j$$

In this equation,  $z_j$  is a decision variable coded into 0 or 1. This variable is determined by a series of latent variables, that is,

$$z_j^* = W_j\gamma + \mu_j$$

Then whether or not one participates in training or makes a decision on something is expressed in the following equation:

$$z_j = 1 \text{ if } z_j^* > 0 ; \text{ otherwise, } z_j = 0$$

Since the *Survey of Migrant Workers' Employment* did not include working hours, we have to use monthly wage income to carry out the regression analysis. Due to variation in the length of individual employment, when monthly wages are used the regression results tend to underestimate returns to schooling. To eliminate the effect of migrant workers' short-term mobility on employment time choice, we did not include in the regression calculation sample materials with less than six months of employment. Using this dataset, we calculate the impact of training on migrant workers' wages. The findings of the regression are presented in Table 7.

In Table 7, Equation (1) treats training as a dummy variable, giving a robust OLS regression result. In Equation (2), we code participation in short-term and formal training as "1" and participation in simple training and no participation in training as "0" to observe the average effects of training. In the treatment effects model, Equations (3) and (4) take into account training decisions and code participation in short-term and formal training as "1" and participation in simple training and no participation in training as "0," to observe the average treatment effects of training. In the regression model involving the decision-making variable, we selected the dummy variables of age, educational level, place of origin and destination as latent variables. In the regression findings, apart from the simple fifteen day training variable in Equation (1), the regression coefficients of all other variables were at the .01 or .05 significance level.

If these different types of training are treated as dummy variables, in regression equation (1), simple fifteen day training did not have a significant effect on migrant workers' earnings, while short-term training lasting fifteen to ninety days and formal training of over ninety days did have a significant effect. Controlling for other variables, the wage level of migrant

29 G.S. Maddala, *Limited-dependant and Qualitative Variables in Econometrics*; W.H. Green, *Econometric Analysis*.

workers receiving short-term training was 6.6 percent higher than that of migrant workers who had received no training. Receiving formal training could increase wage levels by 16.4 percent. Taken together with the previous analysis, this shows that although the simplest form of training has a significant effect on migration, its short duration means that it does little to improve skills. For this reason, estimations of the rate of return to training should treat the simplest training in the same way as no training. To do otherwise could lead to underestimation of the return to training. Regression equation (2) calculates returns to training using the dummy variable method. It shows that migrant workers' average return to participation in short-term and formal training is 9.9 percent.

As the endogeneity issue exists in migrant workers' decisions on training participation, we used the treatment effects model. The findings show that the regression coefficient of the value at risk reaches the .01 significance level, indicating the need for treatment of the training decision variables. In regression equation (3), we use age, sex and years of schooling to control for the effect of individual decisions on whether to participate in training. At the same time, we select the variables of place of origin and migration destination to control for the development of training programs in different regions. Equation (3) shows that the average rate of return to short-term and formal training for migrant workers was 24 percent, higher than the result obtained by using simple instrumental variables in Equation (2). This indicates that skills training that helps form human capital has a significant effect on increasing migrant workers' wage levels.

## **VII. Conclusion**

The lagged development of China's labor market as well as questions of data quality and estimation method mean that findings on the rates of return to schooling among rural migrant labor have always been quite low. Most previous studies based their estimations on annual or monthly earnings data, thus underestimating the level of returns to schooling. Our research shows that with the constant growth of the informal sector in cities and of employment in this sector, failure to distinguish between different types of migrant worker employment will also lead to underestimating returns to schooling. The results of the simple Mincer earnings equation show that returns to schooling for wage earners are about two percentage points higher than for the self-employed.

After introducing demographic and family background variables, we used the expanded Mincer earnings equation to deal with individual heterogeneity. Our findings are consistent with earlier research. As these variables have a linear correlation with schooling, this resulted in a decrease of two percentage points in the rate of the return to schooling. Using parents' years of schooling as an instrumental variable had some effect on the regression equation estimation for the self-employed but none on the equation for wage earners, indicating that it is not an ideal instrumental variable for resolving the issues of educational endogeneity

and individual heterogeneity. After correcting sample selection bias for the expanded Mincer earnings equation, the estimation obtained rates of return to schooling among rural migrant labor of between 5.3 and 6.8 percent; lower than those for urban labor,<sup>30</sup> but similar to the estimates of de Brauw and Rozelle.<sup>31</sup>

From the training perspective, the simplest form of training facilitates migrant workers' repeat migration, but does not have a great effect on improving skills and raising wages. However, short-term and formal training are important determinants of wage levels and skill improvement. Raising migrant workers' employability is the key to resolving their employment problem. Apart from continuing with simple introductory training, future training policy needs to devote its efforts to considering a gradual shift to short-term and formal training, raising migrant workers' skills and income creation ability.

With the rapid acceleration of urbanization, more and more migrant workers are entering the cities. To complete their transition from "farmers" to "urban citizens," it is desirable to accelerate the reform of the household registration system and, at the same time, to use education and training to increase their employability. This could gradually change circular migration to permanent migration. In the course of improving labor market controls, it will be necessary to strengthen protection of migrant workers' rights and interests and totally eliminate the problem of arrears of wages in order to maintain their legitimate rights and lower the risks of migration. In the case of self-employed rural migrant labor, it is necessary to adopt education and training measures designed to improve their management skills, fostering entrepreneurship and the ability to start their own businesses, thus improving their operating space for self-development.

### Notes on Contributors

Wang Dewen, Institute of Population and Labor Economics, Chinese Academy of Social Sciences. E-mail: wangdw@cass.org.cn.

Cai Fang, Institute of Population and Labor Economics, Chinese Academy of Social Sciences. E-mail: caifang@cass.org.cn.

Zhang Guoqing, International Labor Organization Office for China and Mongolia. E-mail: zhangguoqing@ilobj.org.cn.

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31 Alan de Brauw and Scott Rozelle, "Reconciling the Returns to Education in Off-farm Wage Employment in Rural China."

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**Appendixes**

Table 1 Type of employment among migrant workers and wage level

City	Types of employment (percent)			Monthly wage ( <i>yuan</i> )			Hourly Earnings ( <i>yuan</i> /hour)		
	Self-employed	Wage-earner	Total	Self-employed (1)	Wage earners (2)	(3)= (1)/(2)	Self-employed (4)	Wage earners (5)	(6)= (4)/(5)
Shanghai	60.9	39.1	100.0	1,463.1	1153.1	1.27	5.4	5.7	0.94
Wuhan	76.3	23.7	100.0	921.6	805.4	1.14	3.2	4.2	0.77
Shenyang	66.1	33.9	100.0	768.8	825.9	0.93	2.9	3.8	0.76
Fuzhou	52.7	47.3	100.0	1,151.1	850.5	1.35	4.0	4.0	1.00
Xi'an	72.7	27.4	100.0	1,043.4	945.1	1.10	3.5	4.3	0.83
Daqing	56.0	44.0	100.0	950.0	675.3	1.41	3.6	3.4	1.06
Wuxi	42.3	57.7	100.0	1,570.9	1211.6	1.30	6.7	5.7	1.18
Yichang	56.0	44.0	100.0	961.4	648.0	1.48	3.4	2.9	1.18
Benxi	68.2	31.9	100.0	662.3	876.7	0.76	2.9	3.8	0.76
Zhuhai	39.6	60.4	100.0	1,635.7	1190.2	1.37	7.4	5.8	1.29
Baoji	75.7	24.3	100.0	688.2	620.9	1.11	2.4	2.7	0.89
Shenzhen	23.9	76.1	100.0	2,224.9	1733.5	1.28	9.0	9.5	0.95
Five provincial capitals	69.3	30.7	100.0	1,102.4	979.5	1.13	3.9	4.7	0.82
Five medium-sized cities	47.2	52.8	100.0	1,506.1	1171.0	1.29	6.6	5.6	1.17
Total	59.8	40.3	100.0	1,196.4	1150.6	1.04	4.4	5.7	0.77

Source: *Survey on Urban Employment and Social Security in China in 2005*, Institute of Population and Labor Economics of CASS.

Table 2 Training received by migrant workers (%)

Year	2005	2006	Total
No training	42.8	45.3	44.0
Simple training, less than 15 days	24.6	21.5	23.1
Short-term training, 15-90 days	18.9	20.2	19.6
Formal training, more than 90 days	13.7	13.1	13.4
Total	100.0	100.0	100.0
Sample size	5300	5130	10430

Source: *Survey on the Employment of Migrant Workers in 2006 and 2007*, Ministry of Labor and Social Security (MLSS).

Table 3 Estimates of the probability model of employment choice among migrant workers (dprobit model, wage earner = 1)

	(1)	(2)
Sex (Male=1)	0.140	0.138
	(5.25)**	(5.18)**
Marital status (Married=1)	-0.185	-0.186
	(3.65)**	(3.66)**
Marital status (Divorced or widowed =1)	-0.149	-0.148
	(1.51)	(1.50)
Years of schooling (Years)	0.011	0.011
	(2.07)*	(2.00)*
Experience (Years)	-0.010	-0.010
	(2.18)*	(2.17)*
Experience squared (Years squared)	0.000	0.000
	(1.90)	(1.88)
Training received (Yes=1)	0.133	0.132
	(2.34)*	(2.32)*
Family size (Persons)	-0.062	-0.062
	(4.81)**	(4.77)**
Political affiliation (Party member = 1)		0.062
		(0.71)
Number of relatives or friends before moving into cities (Persons)		-0.000
		(0.60)
Intercept	7030	7030

Source: *Survey on Urban Employment and Social Security in China in 2005*, Ministry of Labor and Social Security (MLSS).

Note: (1) The value in the brackets is the robust estimator of  $z$ . Among these, \* represents the .05 significance level while \*\* represents the .01 significance level. (2) The estimator of the dummy variable City is omitted for the sake of brevity.

Table 4 Estimates of the selection model of repeat migration of among migrant workers

	dprobit model (migration=1)	
Sex (Male=1)	0.043	(3.97)**
Years of schooling (Year)	0.007	(2.14)*
Experience (Year)	-0.000	(0.17)
Experience squared	0.000	(0.51)
Simple form of training (Yes=1)	0.085	(6.69)**
Short-term training (Yes=1)	0.112	(8.43)**
Formal training (Yes=1)	0.084	(5.51)**
Year (2007 = 1)	0.004	(0.41)
Low wage arrears (Yes=1)	-0.126	(9.24)**
High wage arrears (Yes=1)	-0.220	(4.02)**
All wages in arrears (Yes=1)	-0.270	(2.43)*
Observables		7960

Source: *Survey on the Employment of Migrant Workers in 2006 and 2007*, Ministry of Labor and Social Security (MLSS)

Note: (1) The value in the brackets is the robust estimator of  $z$ . Among these, \* represents the .05 significance level while \*\* represents the .01 significance level; (2) The estimator of the dummy variables Place of Origin and Place of Destination are omitted for the sake of brevity.

Table 5 Estimates of migrant workers' hourly earnings based on earnings regression equations

	Self-employed			Wage earners			All migrant workers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Years of schooling	0.047	0.026	0.078	0.068	0.047	-0.034	0.056	0.034	0.048
	(4.93)**	(2.59)**	(7.38)**	(14.61)**	(8.49)**	(1.53)	(17.94)**	(10.01)**	(4.91)**
Experience	0.030	0.026	0.025	0.013	-0.010	-0.037	0.015	0.006	0.005
	(3.22)**	(2.20)*	(4.64)**	(3.62)**	(1.76)	(3.94)**	(5.82)**	(1.58)	(1.11)
Experience squared	-0.001	-0.001	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000
	(3.30)**	(2.47)*	(4.33)**	(3.86)**	(0.13)	(1.88)	(5.98)**	(2.93)**	(2.59)**
Sex (Male=1)		0.270	0.211		0.293	0.359		0.295	0.274
		(5.66)**	(8.93)**		(10.04)**	(10.17)**		(16.99)**	(14.29)**

Marital status (Married=1)		-0.040	-0.018		0.049	0.219		-0.000	-0.026
		(0.31)	(0.30)		(1.17)	(3.49)**		(0.00)	(0.77)
Political affiliation (Party member=1)		-0.171	-0.211		0.103	0.195		-0.053	-0.061
		(1.24)	(2.75)**		(1.27)	(2.20)*		(0.97)	(1.08)
Training (Yes=1)		-0.052	-0.094		-0.042	-0.034		-0.052	-0.036
		(0.55)	(1.09)		(0.72)	(0.56)		(1.08)	(0.74)
Years of schooling of father		0.007			0.001			0.003	
		(0.80)			(0.14)			(0.97)	
Years of schooling of mother		0.029			-0.003			0.018	
		(2.98)**			(0.58)			(5.78)**	
Intercept	0.509	0.527	0.371	0.737	0.995	1.956	0.685	0.771	0.910
	(3.43)**	(2.67)**	(2.53)*	(11.57)**	(12.05)**	(7.67)**	(15.35)**	(13.83)**	(7.69)**
Observables	3909	3617	3617	2429	1987	1987	6343	5609	5609
R-squared	0.19	0.23	0.18	0.24	0.28	0.20	0.22	0.25	0.25

Source: *Survey on Urban Employment and Social Security in China in 2005*, Ministry of Labor and Social Security (MLSS)

Note: (1) The value in the brackets is the robust estimator of  $t$  or  $z$ . Among these, \* represents the .05 significance level while \*\* represents the .01 significance level. (2) The estimator of the dummy variable City is omitted for the sake of brevity.

Table 6 Estimates of migrant workers' wages based on Heckman selection model

	(1)	(2)	(3)	(4)
	Wage equation	Career choice equation	Wage equation	Career choice equation
Years of schooling (Year)	0.068 (13.51)**	0.017 (2.35)*	0.053 (10.11)**	0.017 (2.35)*
Experience (Year)	0.008 (1.55)	-0.034 (5.03)**	0.000 (0.09)	-0.034 (5.03)**
Experience squared	-0.000 (3.02)**	0.001 (5.27)**	-0.000 (2.04)*	0.001 (5.27)**
Family size		-0.204 (11.37)**		-0.204 (11.37)**
Marital status		-0.570 (8.42)**	0.062 (1.06)	-0.570 (8.42)**
Sex (Male=1)		0.026 (0.73)	0.312 (11.91)**	0.026 (0.73)
Political affiliations (Party member=1)		0.004 (0.03)	0.074 (0.81)	0.004 (0.03)
Training received (Yes=1)		0.323 (3.89)**	0.088 (1.68)	0.323 (3.89)**
Years of schooling of father			0.005 (1.27)	
Years of schooling of mother			0.003 (0.62)	
Intercept	0.802 (9.80)**	0.958 (7.97)**	0.725 (8.80)**	0.958 (7.97)**
Inverse Mills Ratio	0.159 (2.53)**		0.20 (2.13)*	
Observables	6131	6131	6131	6131

Source: *Survey on Urban Employment and Social Security in China in 2005*, Ministry of Labor and Social Security (MLSS)

Note: (1) The value in the brackets is the robust estimator of  $z$ . Among these, \* represents the .05 significance level while \*\* represents the .01 significance level; (2) The estimator of the dummy variable City is omitted for the sake of brevity.

Table 7 Regression equation on the impacts of training on earnings

	OLS estimates		Treatment effects model	
	(1)	(2)	(3)	(4)
Age				-0.010 (4.01)**
Years of schooling	0.024 (7.88)**	0.027 (8.58)**	0.017 (5.47)**	0.200 (19.97)**
Experience	0.021 (11.65)**	0.021 (11.54)**	0.022 (12.23)**	
Experience squared	-0.000 (7.59)**	-0.000 (7.56)**	-0.000 (8.35)**	
Male	0.174 (19.15)**	0.179 (19.69)**	0.173 (17.83)**	0.084 (2.22)*
Simple form of training	0.014 (1.32)			
Short-term training	0.066 (5.37)**			
Form training	0.164 (10.28)**			
Variable of Training decision		0.099 (10.03)**	0.240 (8.47)**	
Dummy variables of years	0.159 (18.03)**	0.157 (17.76)**	0.156 (17.65)**	
Dummy variable: migrant workers' places of origin	Yes	Yes	Yes	Yes
Dummy variable: migrant workers' destinations				Yes
Intercept	6.319 (184.16)**	6.305 (184.31)**	6.210 (181.95)**	-2.496 (12.51)**
Hazard			-0.0949 (5.31)	
Observables	6747	6747	6747	6747
R-squared	0.21	0.21		

Source: *Survey of the Employment of Migrant Workers in 2006* and *Survey of the Employment of Migrant Workers in 2007*, Ministry of Labor and Social Security (MLSS).

Note: (1) The value in the brackets is the robust estimator of  $t$  or  $z$ . Among these, \* represents the .05 significance level while \*\* represents the .01 significance level.

—Translated by Liu Hui  
Revised by Sally Borthwick