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Experience, tenure and gender wage difference: evidence from China

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ABSTRACT

This paper studies the returns to general labour market experience and firm-specific tenure, using data from China. Specifically, it focuses on explaining the gender wage difference from the perspective of general human capital and specific human capital. It applies the Heckman maximum likelihood estimator and Topel two-step estimation methodology to correct sample selection bias and individual heterogeneity. After correcting the errors, the authors find that returns to experience are higher for men than women, especially for married men and women. Furthermore, the return to tenure is higher than that to general experience. For men, the former is about 6% higher than the latter. But for women, tenure contributes 7–8% more to the wage growth than experience. The return of general experience mainly contributes to gender wage difference in China. Empirical results also show that the cross section analysis downward biases the returns to potential experience and a simple Topel-2S estimation in the panel study upward biases the returns.

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1. Introduction

The labour market for women has changed substantially in the world. Women's labour force participation rate has increased. Women gain better payment and more promotions and obtain a better economic status. According to *The Global Gender Gap Report 2015 (2015)*, the female labour force participation rate in China was 46.63% in 1982 and reached 73% in 2015, which was the highest in the world. However, the gender wage gap persists, even is enlarged. The *Green Book of Population and Labor 2016 (2016)* released by the Population and Labor Economics Institute of the Chinese Academy of Social Sciences reports that the gender pay gap in China is widening. In 1990, women made on average 77.5% of men's salaries, but the rate dropped to 65.8% in 2010. The *Report of China's Gender Wage Gap 2016*, published on the web of Boss Zhipin which is a recruiting website in China, also confirms that the average income before tax for females was 4449 RMB in 2016, which

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was about 22.3% lower than that of males' average income. Furthermore, the higher the income level, the wider the gap. These numbers indicate that women's relative economic status may be worse in terms of wage rate. The report says that 56% of the wage gap could be explained by occupations, regional differences, working experience and education level. When the working experience increases by one year, the income will increase by 6.3% for females and 7.5% for males. Meanwhile, when education increases by one level, the income will increase by 9.6% for females and 8.3% for males. Therefore, working experience widens the gender wage gap, while education does the opposite. If this is the case, it is necessary to revisit the wage experience profile to explore the channel through which gender wage gap is widened. How wages increase with experience across different subpopulations not only matters to employees, but also poses important implications to understanding the wage structure.

Becker (1975) differentiates general labour experience and job-specific human capital (also called tenure). The theory of human capital argues that general experiences help to raise the productivity for most jobs in the market, while tenure raises the productivity at the current job. Therefore, employers have a strong incentive to invest in specific training. Employers are more likely to hire male employees in consideration of the higher labour market attachment of male workers. According to theory, during the training process the pay may be lower on average, but the growth rate of wages will be higher in the long run. The delayed payment mechanism could decrease the turnover rate. On the other hand, the theory also indicates that the costs of job mobility could be high.

In order to examine the latitude that labour market affects gender wage difference, we argue that firm-specific experience should be differentiated from general labour market experience (Abraham et al., 1987; Becker, 1975; Dobbie, MacMillan, & Watson, 2014; Topel, 1991). However, sample selection bias and personal heterogeneity should be taken into consideration. There are two contributions made by this study. First, we contribute to the methodological literature on estimating wage growth. We address the sample selection bias by applying the Heckman maximum likelihood estimator (MLE) and incorporate the methodology into the Topel-2S to solve the personal heterogeneity problem. We try to examine the extent to which the potential experience and tenure affect men and women's wage growth. Second, we examine whether tenure contributes to gender wage gap. Although our study is based on the data of China, the gender wage gap exists universally in the world. Understanding the wage experience profile has implications for government policies on the labour market, such as how to invest human capital, and how to establish an incentive mechanism of labour demand and labour supply.

The rest of the paper is organised as follows. [Section 2](#) reviews the literature. [Section 3](#) describes the data and variables. [Section 4](#) provides a discussion on empirical methodology. [Section 5](#) reports the empirical result and robustness tests. [Section 6](#) concludes.

2. Literature review

The Mincer model lays a foundation for studies on human capital in the area of labour economics. However, most early studies on wage growth only include experience in regression models without paying enough attention to tenure, which results

in underestimating the return to training and overestimating the return to formal education (Regan & Oaxaca, 2009). If this is the case, government might invest too much in school education, but too little in professional training.

Following the Mincer model, a large body of recent literature has documented a discussion of market returns of experience and tenure. There are mainly two streams of literatures. The first group of literature has been making efforts to improve the empirical results. Most agree that the overall return to human capital is higher for men than for women (Light & Ureta, 1995; Munasinghe, Reif, & Henriques, 2008; Orłowski, 2010). However, when decomposing the return to general human capital and firm-specific human capital, conflict results were reported. Some found that both experience and tenure statistically influenced one's wage rate (Topel, 1991), while some argued that tenure had little impact on one's wage (Abraham & Farber, 1987; Orłowski, 2010; Strobl & Walsh, 1999; Williams, 1991). Some found that returns to experience and tenure were higher for men than for women (Munasinghe et al., 2008), while some found the opposite results (Becker & Lindsay, 1994; Coleman, 1998).

Dustmann and Meghir (2005) used a sample of young workers in Germany and found positive returns to experience and tenure for skilled workers on wage growth, and no impact for unskilled workers. Furthermore, they also found that the return to firm tenure was substantial. Orłowski (2010) used data from Germany to examine returns to the experience and tenure from a lifecycle perspective. The author found very low returns to tenure for all workers and thus concluded that most wage growth could be explained by the accumulation of general experience. The author also found significantly lower returns to experience for women than men. Munasinghe et al. (2008) used the National Longitudinal Survey of Youth (NLSY) panel data to examine returns to experience and tenure. They used the information of actual working experience asked in the survey and the current job tenure in the wage equation. The authors found that among more educated work, the return to tenure is lower for women than for men. Williams (1991) found that general market experience increased wages significantly over a career, but tenure only increased wages in the first few years of a career. Becker and Lindsay (1994) found that since women were more likely to leave a job than men, an efficient cost-sharing model implied a higher return to tenure for females than males. However, Strobl and Walsh (1999) updated their study and found no gender difference in the return to tenure. Coleman (1998) used the British New Earnings Survey in the study and found that females have higher returns to tenure than males. He argued that this was because the starting salaries were usually low for women and that some catch-up attempts had been made by the unions and government to drive up the wage rate. Meanwhile, market segmentation could also, to some extent, explain the results, since women may be concentrated in jobs where tenure is a relatively more important determinant of earnings. Dobbie et al. (2014) used Australian panel data and argued that market experience and occupational tenure matter to wage growth, while job tenure does not show effects. They argued that occupational tenure somehow negated the job tenure effect. Battisti (2016) applied data of young Italian workers and found that wage returns to industry experience were much higher than wage returns to job seniority.

Lazear (2009) argues that there is no clear line between the returns to general human capital and to the specific human capital. Individuals hold a set of skills that matches each

employer. The growth of one's wage greatly depends on how well the skills match the requirement of the current employer. Recent studies, such as Gathmann and Schonberg (2010) and Yamaguchi (2012), followed similar logics and tried to provide new insights in understanding the impact of general and specific human capital on labour market.

The second group focuses on the methodology used to solve the endogeneity problem. Ordinary least squares (OLS) estimation was criticised by most studies for biased estimates, since both experience and tenure might correlate with error terms. Thus, instrumental variables were applied in many studies (Light & Ureta, 1995; Sulis, 2014). Light and Ureta (1995) measured the work experience by calculating the fraction of time worked during each year of the career, and used Instrumental Variable (IV) estimation in the study. They found that return to tenure was three times larger for women when comparing with men. However, the study is criticised for using IV estimation. Sulis (2014) studied the return to experience and tenure for Italian young men. The author found that OLS estimation downward biased the returns to both. Topel (1991) once argued that instrumental variables might consistently underestimate the return to tenure. Therefore, augmented instrumental variables are applied in the analysis, including the IV estimation proposed by Altonji and Shakotko (1987) and the two-stage first differencing estimation proposed by Topel (1991) (Munasinghe et al., 2008; Orłowski, 2010).

The measurement error problem was also discussed (Antecol & Berdard, 2002, 2004; Regan & Oaxaca, 2009) to help to improve the results. It arises when potential experience is used instead of actual experience in empirical analysis. Regan and Oaxaca (2009) used data from the 1979 National Longitudinal Survey of Youth and Panel Study of Income Dynamics to predict actual experience. They then extended the predicted actual experience to a data set including both male and female workers and found that potential experience did bias the results by overestimating the return of schooling and underestimating the return to work experience.

In sum, critical problems that contribute to ambiguous results are personal heterogeneity and sample selection bias. The source of individual heterogeneity is individuals' different incentives to attend the labour market and the possibility that high ability workers are more likely to stay in the labour market and, hence, have more of both general and firm-specific experience. Heterogeneity could originate from different living habits, and different propensities to quit or to be absent once workers are employed (Weiss, 1995). Selection bias arises when only those employed are observed and included in wage regression models (Heckman, 1979). In consideration of the problem that fixed or random effect estimation would not provide efficient estimates (Wooldridge, 2009) because of the constant variation of experience and tenure, we apply Topel-2S (1991) estimation in this study.

3. Data analysis

3.1. Data

We apply the data of China Family Panel Studies (CFPS) between 2010 and 2014. The dependent variable is the logarithm of the worker's hourly wage. The interested variables are potential experience (*exp*) and seniority (*tenure*). Potential work

Table 1. Descriptive statistics.

Variable	Men		Women		Married men		Married women	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Log hourly wage	2.122	0.712	1.9	0.728	2.15	0.708	1.905	0.722
Married	0.843	0.364	0.831	0.375				
Education	10.111	4.056	10.55	4.186	9.954	4.066	10.283	4.264
Experience	21.332	11.425	17.412	9.764	24.025	10.127	20.037	8.479
Tenure	9.605	9.827	7.223	7.978	10.923	10.069	8.299	8.292
Union member	0.095	0.293	0.075	0.264	0.103	0.305	0.083	0.276
Party member	0.187	0.39	0.919	0.289	0.209	0.407	0.096	0.295
Hukou	0.562	0.496	0.578	0.494	0.576	0.494	0.606	0.489
Health status	2.511	0.61	2.488	0.603	2.477	0.622	2.442	0.616
Public sector	0.205	0.404	0.216	0.411	0.221	0.415	0.229	0.42
State-owned firm	0.227	0.419	0.156	0.363	0.238	0.426	0.164	0.37
Private sector	0.439	0.496	0.495	0.5	0.415	0.493	0.48	0.5
Other	0.129	0.335	0.133	0.34	0.128	0.334	0.127	0.333
Share	0.088	0.145	0.07	0.139	0.1	0.148	0.083	0.147
Number of observations	3281		2187		2766		1818	

Data source: 2010 CFPS data.

experience is calculated by subtracting six and the years of education from a person's age if he/she has more than 10 years of education. For those who receive less than 10 years of education, the experience is calculated by subtracting 16 from their age. Other control variables include: individual's marital status, years of education (*edu*), union member, non-agricultural residency (*hukou*), Communist Party member (*member*), health status, individual's occupation, industry, types of enterprises' ownership, and province dummies. Descriptive data are listed in Table 1.

3.2. Contributions of variables to wage inequality

We apply the decomposition methodology proposed by Fields and Yoo (2000)¹ to identify how much income inequality is explained by each explanatory variable in a standard semi-log wage regression model. Let

$$\ln W_i = a'Z_i \quad (1)$$

where $a = [\alpha \beta_1 \beta_2 \dots \beta_j \ 1]$, and $Z_i = [1 \ x_{i1} x_{i2} \dots \ x_{ij} \varepsilon_i]$. By taking the variance of both sides of Equation (1), the left-hand side represents wage inequality. The equation could be rearranged in the following form:

$$S_j(\ln W_i) = \frac{\text{cov}(a_j Z_j, \ln W)}{\sigma^2(\ln W)} = \frac{a_j \sigma(Z_j) \text{cor}(Z_j, \ln W)}{\sigma(\ln W)} \quad (2)$$

where $S_j(\ln W_i)$ refers to 'relative inequality weight'. In terms of Equation (2), we calculate the contribution to wage inequality for each explanatory variable. Table 2 shows that, under the OLS regression model, 8% of wage inequality is attributed to the years of education. Moreover, 3% is attributed to tenure and 0.5% to potential experience. For married employees, 7.7, 3.2, and 1.1% of wage inequality is attributed

Table 2. Decomposition of wage inequality.

Variable	All		Married	
	OLS	MLE	OLS	MLE
Gender	0.023	0.024	0.029	0.029
Married	0.003	0.001	N/A	N/A
Edu	0.08	0.163	0.077	0.163
Exp	0.005	0.012	0.011	0.018
Tenure	0.03	0.032	0.032	0.033
Union	0.003	0.007	0.003	0.007
Member	0.009	0.02	0.007	0.021
Hukou	0.014	0.031	0.015	0.034
Health	0.001	0.002	0.001	0.003
Firm type	0.029	0.028	0.028	0.027
Occupation	0.063	0.056	0.067	0.059
Industry	0.017	0.016	0.016	0.017
Region	0.124	0.124	0.108	0.108
Residual	0.599	0.483	0.605	0.481

Notes: “Exp” represents the contribution of experience and its quadratic term to the wage inequality, as does “Tenure.” Other controlled variables include: firm-type dummy (3), occupation dummy (6), industry dummy (19), and region dummy (24). Data source: 2010 CFPS.

to years of education, tenure, and potential experience, respectively. This indicates that experience and tenure contribute more to wage inequality for married workers.

If we correct the selection bias with Heckman MLE, the contribution of education doubles for both the overall and married samples. Tenure still contributes more to general wage inequality than potential experience. Compared with the results from the OLS model, the contributions of most variables increase and the contribution of residual to wage inequality decreases by about 20%.

We subsequently apply Oaxaca (1973) and Blinder (1973) methodology² to analyse the contribution each variable makes to gender wage inequality. The estimated wage equations for males and females can be written as in Equations (3) and (4):

$$\ln \bar{W}^m = \hat{\alpha}^m + \hat{\beta}^{m'} \bar{X}^m \tag{3}$$

$$\ln \bar{W}^f = \hat{\alpha}^f + \hat{\beta}^{f'} \bar{X}^f \tag{4}$$

where the $\ln \bar{W}^m$ is the average wage for males; $\hat{\alpha}^m$ is the estimated intercept term; $\hat{\beta}^{m'}$ is a row vector of estimated slope coefficients for the set of regressors in the wage equations; and \bar{X}^m is a column vector of regressor means. Equation (4) is for females. As such, the mean difference of log wages between males and females could be specified as

$$\begin{aligned} \ln \bar{W}^m - \ln \bar{W}^f &= \hat{\alpha}^m - \hat{\alpha}^f + \hat{\beta}^{m'} \bar{X}^m - \hat{\beta}^{f'} \bar{X}^f \\ &= \hat{\beta}^{*'} (\bar{X}^m - \bar{X}^f) + (\hat{\beta}^{m'} - \hat{\beta}^{*'}) \bar{X}^m + (\hat{\beta}^{*'} - \hat{\beta}^{f'}) \bar{X}^f + \hat{\alpha}^m - \hat{\alpha}^f \end{aligned} \tag{5}$$

where $\hat{\beta}^{*'}$ represents a row vector of constructed non-discriminatory coefficients for the set of regressors. Consequently, the first term on the right-hand side of Equation (5) is the part ‘explained’ by group differences, and the rest of the terms on

Table 3. The Oaxaca–Blinder decomposition of the gender wage gap.

	All		Married	
	OLS	MLE	OLS	MLE
Prediction_male	2.122*** (0.012)	1.793*** (0.026)	2.150*** (0.013)	1.819*** (0.028)
Prediction_female	1.901*** (0.016)	1.444*** (0.040)	1.905*** (0.017)	1.420*** (0.044)
Difference	0.221*** (0.020)	0.349*** (0.048)	0.245*** (0.022)	0.399*** (0.053)
Explained	0.033** (0.014)	0.033** (0.014)	0.042*** (0.016)	0.042*** (0.016)
Unexplained	0.188*** (0.014)	0.316*** (0.045)	0.203*** (0.015)	0.357*** (0.050)

Notes: *** and ** represent significance at the 1 and 5% levels, respectively. Standard errors are in parentheses. Data source: the 2010 CFPS data.

the right-hand side are the ‘unexplained’ part. The sum of the ‘explained’ and ‘unexplained’ parts is the so-called ‘two-fold’ decomposition (Jann, 2008).

When estimating the effects of discrimination, however, the index number problem (Oaxaca, 1973) is always involved in the analysis. Therefore, an index is required to eliminate the effect of price differences between the two groups. Economists have put forward different methods to select non-discriminatory coefficients. Oaxaca (1973) suggests using the estimated slope coefficients of males or females as $\hat{\beta}^{*f}$. Reimers (1983) adopts the average coefficients over both groups to replace it. Cotton (1988) proposes to weight the coefficients of both group sizes (males and females). Neumark (1988) advocates using the coefficients from a pooled regression over both groups to capture the non-discriminatory coefficients. In this paper, we follow the approach proposed by Oaxaca and Ransom (1994), in which a weighting matrix is constructed to acquire $\hat{\beta}^{*f}$. The coefficients are specified as

$$\hat{\beta}^* = (\bar{X}^{m'}\bar{X}^m + \bar{X}^{f'}\bar{X}^f)^{-1}(\bar{X}^{f'}\bar{X}^f)\hat{\beta}^m + \left[\mathbf{I} - (\bar{X}^{m'}\bar{X}^m + \bar{X}^{f'}\bar{X}^f)^{-1}(\bar{X}^{f'}\bar{X}^f) \right] \hat{\beta}^f \quad (6)$$

where \mathbf{I} is the identity matrix.

Table 3 lists results of the Oaxaca–Blinder wage decomposition under the OLS and Heckman MLE regression models. After correcting the sample selection bias, the unexplained part still plays the dominant role (0.316 log points). The difference between the unexplained and explained parts indicates that gender wage difference is still a serious problem in the labour market in China.

Table 4 reports the partial contribution of each variable to the gender wage difference (see Table 4). The partial contribution of experience and education to the explained part and the unexplained part are significant and negative, meaning that both help to narrow the gender wage gap. The partial contribution of tenure is 0.027 log points to the explained part, indicating that tenure may enlarge the gender wage gap.

4. Empirical methodology

Our primary regression model is based on an expanded Mincer wage function as follows. Potential experience and tenure are both included in the function to correct

Table 4. The Blinder–Oaxaca decomposition of the gender wage gap.

Variable	Explained		Unexplained			
			All		Married	
	All OLS	Married OLS	OLS	MLE	OLS	MLE
Exp	−0.024*** (0.005)	−0.025*** (0.006)	0.052 (0.073)	−0.199** (0.083)	0.077 (0.090)	−0.307*** (0.103)
Tenure	0.027*** (0.004)	0.030*** (0.005)	−0.004 (0.027)	−0.009 (0.026)	0.012 (0.031)	0.008 (0.030)
Edu	−0.016*** (0.004)	−0.012** (0.005)	−0.066 (0.059)	−0.252*** (0.073)	−0.06 (0.061)	−0.251*** (0.077)
Constant			−0.007 (0.122)	0.325* (0.172)	0.004 (0.142)	0.766*** (0.212)

Notes: “Exp” represents the contribution of experience and its quadratic term to the wage inequality, as does “Tenure.” Other controlled variables include: firm-type dummy (3), occupation dummy (6), industry dummy (19), and region dummy (24). We only report the main results of experience, tenure, and education. Since the Heckman MLE did not change the results on the basis of the OLS estimation, we only report results of OLS estimates. Data source: 2010 CHPS. ***, **, and * represent significance at the 1, 5, and 10% levels. Standard errors are in parentheses.

selectivity bias. Square terms for both are also included to examine their nonlinear correlations with log wage:

$$\ln W_i = \alpha + \beta_1 \exp_i + \beta_2 \exp_i^2 + \beta_3 \text{tenure}_i + \beta_4 \text{tenure}_i^2 + \sum_k \delta_k D_{ik} + \varepsilon_i \quad (7)$$

where $\ln W_i$ is the log of hourly wage of individual i ; \exp_i is individual i 's potential experience, which is defined as the general human capital obtained on the labour market; \exp_i^2 is the square term of potential experience; tenure_i is one's seniority in the current job; tenure_i^2 is the square term of one's tenure; D_{ik} represents other control variables, including personal characteristics, labour market information; $\beta_1, \beta_2, \beta_3, \beta_4,$ and δ_k are parameters; α is the constant term; and ε_i is the error term. The sample selection bias that arises when female workers exhibit a lower attachment to the labour market (i.e., unemployed at the time of the survey) may be excluded from the sample. Such a problem could be seen as an omitted variable problem (Heckman, 1979). To correct the sample selection in the cross section and panel data analysis, we apply the Heckman two-step MLE. The selection equations are as follows:

$$P(\text{participation}_i = 1 | X_i) = \Phi(X_i' \rho) \quad (8)$$

Individual i 's decision to participate in the labour market depends on a set of personal characteristics X_i , including not only personal characteristics, but also variables that affect the employee's decision to enter the labour market without affecting the wage growth. We use variable *share*, which represents the percentage of family members who are under 7 and above 65 years old.

We also construct a longitudinal data analysis. Compared with the cross section analysis, panel data take into consideration the accumulation of human capital instead of the human capital at a certain time point. Moreover, the cross section analysis failed to control for the individual fixed effect. The source of individual heterogeneity could be not only individuals' different incentives to attend the labour market, but also the possibility that higher ability workers are more inclined to stay in the labour

market and, hence, have more of both general and firm-specific experience (Altonji & Williams, 2005). Therefore, a panel study has the advantage of controlling for the individual-specific error. However, simply using the fixed or random effect estimation would not provide efficient estimates in studying the return to experience (Wooldridge, 2009) because the variation of experience and tenure will be constant as long as they are included in the sample, which is two years in our study. Therefore, we apply Topel-2S estimation, which is detailed in Topel's (1991) work.

Besides the individual fixed effects and endogeneity problem, sample selection bias is still a problem not taken into consideration by studies that use Topel-2S to examine returns to experience and tenure. Topel-2S will provide unbiased results if, and only if, employees who start a new job or never change their job are randomly selected, which is difficult to satisfy. Therefore, not considering the selection bias might bias the return to experience upward (Williams, 2009), since the observations included in the study are those who exhibit a high attachment to current jobs. Employees who have a lower attachment to their job or to the labour market are excluded from the data. Our study incorporates the Heckman MLE to correct selection bias. The following section briefly demonstrates this method when applying it to our study. We start with the Mincer wage equation in Equation (9).

$$\ln W_{ijt} = \alpha + \beta_1 \exp_{ijt} + \beta_2 \exp_{ijt}^2 + \beta_3 \text{tenure}_{ijt} + \beta_4 \text{tenure}_{ijt}^2 + \sum_k \delta_k D_{ijtk} + \varepsilon_{ijt} \quad (9)$$

where $\ln W_{ijt}$ is the log hourly wage for individual i when working at job j at time t . \exp_{ijt} is individual i 's potential work experience, and tenure_{ijt} is i 's tenure at job j . \exp_{ijt}^2 and tenure_{ijt}^2 are quadratic forms of experience and tenure. D_{ijtk} includes all other control variables. $\beta_1, \beta_2, \beta_3, \beta_4$, and δ_k are parameters. α is the constant term and ε_{ijt} is the error term. The within job wage growth could be calculated by first differencing the wage equation, which would eliminate the fixed job and individual effects. Let

$$\exp_{ijt} = \exp_0 + \text{tenure}_{ijt} \quad (10)$$

where \exp_0 is the initial potential experience, and total experience is the sum of the initial experience and tenure. Considering the wage growth of those not willing to change their current job in the next iteration, we have the following result:

$$\ln W_{ijt} - \ln W_{ijt-2} = 2(\beta_1 + \beta_3) + \beta_2(4 \exp_{ijt} - 4) + \beta_4(4 \text{tenure}_{ijt} - 4) + \varepsilon_{ijt} - \varepsilon_{ijt-2} \quad (11)$$

Because the panel survey is conducted over two years, the last period is represented by $(t - 2)$. If $E(\varepsilon_{ijt} - \varepsilon_{ijt-2}) = 0$, an OLS analysis of Equation (11) provides unbiased estimates of $(\widehat{\beta_1 + \beta_3})$, $\widehat{\beta_2}$ and $\widehat{\beta_4}$. By plugging Equation (10) into Equation (9) and rearranging it, we have

$$\ln W_{ijt} - (\widehat{\beta_1 + \beta_3}) \text{tenure}_{ijt} - \widehat{\beta_2} \exp_{ijt}^2 - \widehat{\beta_4} \text{tenure}_{ijt}^2 = \alpha + \beta_1 \exp_0 + \sum_k \delta_k D_{ijtk} + \varepsilon_{ijt} \quad (12)$$

We could obtain $(\widehat{\beta}_1 + \widehat{\beta}_3)$, $\widehat{\beta}_2$ and $\widehat{\beta}_4$ by estimating Equation (11) and $\widehat{\beta}_1$ by estimating Equation (12). Then we subtract $\widehat{\beta}_1$ from $(\widehat{\beta}_1 + \widehat{\beta}_3)$ to obtain $\widehat{\beta}_3$.

Again, the selection bias still exists since the data include only individuals that do not change jobs during any two consecutive surveys. Therefore, we incorporate Heckman MLE to the Topel-2S estimation to avoid the selection bias problem:

$$P(\text{change}_{ijt} = 1 | X_{ijt}) = \Phi(X'_{ijt}\rho) \quad (13)$$

where change_{ijt} is a binary variable and equals 1 if one changes job between any two consecutive surveys and 0 otherwise. X_{ijt} is a vector of the explanatory variables, which includes not only independent variables in Equation (12), but also variables that affect the employee's decision to change his/her current job without affecting his/her wage. Therefore, we construct a dummy variable that equals 1 if one has a second job, and 0 otherwise. We run regressions for Equations (12) and (13) to get unbiased estimates of returns to experience and tenure with panel data.

5. Results and discussion

5.1. Empirical results

In Table 5, the likelihood ratio test indicates that sample selection bias exists for all groups. The results show that potential experience has an inverse U-shaped correlation with wage growth. The return to experience is higher for females than males, and is higher for married women than married men. Tenure has a significant and positive influence on wage growth for all groups. The insignificant square terms of tenure indicate a linear correlation with wage growth, which is different from some previous studies using data from foreign countries (Bratsberg & Terrell, 1998; Hersch & Reagan, 1990; Williams, 1991). Guasch and Weiss (1982) argue that deferred compensation payment could discourage employees with low market attachment from applying for the job and is responsible for the linear relationship. Chow-tests show the return to experience is higher for women than men, but no gender difference in the return to tenure.

Table 6 lists the results for cross section and panel analysis with and without MLE applied. Topel-2S estimation with MLE applied shows that all coefficients become smaller. An increase in experience raises the wage by 5.9% for men and 4.6% for women, and by 6% for married men and 2.8% for married women. Furthermore, the gender difference of the return to experience is increasing for married employees. This is because women traditionally undertake more housework than men, and the return to experience for married women may depreciate even faster and contribute to the increasingly wide gender wage gap. Also, women are required to retire at 55 in China, which may lower the expectation of the return to experience and thus decrease the incentive for human capital investment for women. As a result, the lower expectation decreases one's productivity and wage growth.

Table 5. Heckman MLE with cross section analysis (2010).

Variable	Men	Women	Chow-test	Married men	Married women	Chow-test
Experience	0.023*** (0.005)	0.052*** (0.008)	8.416 [0.004]	0.010* (0.006)	0.045*** (0.009)	10.08 [0.001]
Experience squared	-0.001*** (0.0001)	-0.002*** (0.0002)	11.809 [0.001]	-0.001*** (0.0001)	-0.002*** (0.0002)	12.264 [0.000]
Tenure	0.013*** (0.004)	0.012** (0.005)	0.025 [0.874]	0.014*** (0.004)	0.009* (0.005)	0.465 [0.495]
Tenure squared	-0.0001 (0.0001)	0.0001 (0.0002)	0.363 [0.547]	-0.0001 (0.0001)	0.0001 (0.0002)	0.927 [0.336]
Constant	0.06 (0.184)	-0.574** (0.262)	5.189 [0.023]	0.314 (0.200)	-0.670** (0.282)	9.78 [0.002]
Other variables controlled	Yes	Yes		Yes	Yes	
Selection equation						
Share	-0.165 (0.111)	-0.961*** (0.126)	22.594 [0.000]	-0.11 (0.121)	-0.873*** (0.128)	18.711 [0.000]
LR	65.48 [0.000]	60.555 [0.000]		58.206 [0.000]	52.798 [0.000]	
Number of observations						
Uncensored	3281	2187		2766	1818	
Censored	3668	5023		3049	4619	

Notes: Only interested variables are listed in the table. Other controlled variables include: firm-type dummy (3), occupation dummy (6), industry dummy (19), and region dummy (24). ***, ** and * represent significance at the 1, 5, and 10% levels. Standard errors are in parentheses. *p*-Values are in brackets. The selection equation also includes personal characteristics variables of wage equation but they are not reported. Data source: 2010 CFPS.

Coefficients for tenure increase when Topel-2S and Heckman MLE are applied. Thus, the Topel-2S estimation without correcting the sample selection bias may over-predict the return to the experience and downward bias the return to tenure.

5.2. Robustness test

We conduct robustness tests in this session. The first test, listed in Table 7, considers the impact of the number of children. Since women usually take more of the responsibilities regarding housework and child care, the number of children under 16 is one of the reasons women have lower attachment to the labour market, and, as result, the return to experience for women is lower than for men. When controlling for the number of children under 16, the results show that the return to experience for women is even higher, which is expected. However, the result is consistent with previous studies in that the return to experience is higher for women than men, while the return to tenure shows no difference between men and women. Overall, the return to experience is consistently higher than that to tenure.

The second test in Table 7 uses the employee's age as a proxy for potential experience. It is argued that potential experience assumes that one enters the labour market after completing schooling and stays on the market without interruptions, and therefore experience increases with age. Therefore, age can be used instead of experience. Although we obtain the same conclusion, the coefficients are generally higher than results from the first test (see Table 7). This is because age is also a wage determinant; therefore, the estimate of age includes not only the return to experience but also the return to age. We also use 2012 and 2014 CFPS data for the cross section analysis in the third and fourth tests. Again, previous results are confirmed.

Table 6. Estimates of wage regression (2010–2014).

		Men (1)	Women (2)	Chow-test (3)	Married men (4)	Married women (5)	Chow-test (6)
Cross section analysis							
OLS	Experience	0.010** (0.005)	0.007 (0.007)	0.089 [0.766]	0.001 (0.006)	−0.005 (0.007)	0.448 [0.503]
	Tenure	0.014*** (0.004)	0.012** (0.005)	0.027 [0.869]	0.015*** (0.004)	0.010* (0.005)	0.4 [0.527]
Heckman MLE	Experience	0.023*** (0.005)	0.052*** (0.008)	8.416 [0.004]	0.010* (0.006)	0.045*** (0.009)	10.08 [0.001]
	Tenure	0.013*** (0.004)	0.012** (0.005)	0.025 [0.874]	0.014*** (0.004)	0.009* (0.005)	0.465 [0.495]
Panel analysis							
Topel-2S	Experience	0.073*** 0	0.064*** 0	2.985 [0.084]	0.075*** 0	0.046*** 0	5.853 [0.016]
	Tenure	0.11	0.097	–	0.109	0.093	–
Heckman MLE	Experience	0.059*** 0	0.046*** 0	32.694 [0.000]	0.060*** 0	0.028*** 0	38.439 [0.000]
	Tenure	0.124	0.115	–	0.123	0.111	–

Notes: ***, ** and * represent significance at the 1, 5, and 10% levels, respectively. Standard errors are in parentheses. *p*-Values are in brackets. In panel data analysis, estimates for tenure are calculated by two steps, thus no standard errors are reported and no Chow-test was conducted. Data source: 2010–2014 CFPS data.

6. Conclusions

As discussed in the main text, personal heterogeneity and selection bias were the main problems in previous studies, which caused mixed results. By applying the data of China, we found that cross section analysis downward biases the results and a simple Topel-2S estimation in panel study overestimates the return to potential experience.

After correcting the sample selection bias and personal heterogeneity problems, our results show the following findings. First of all, potential experience has a positive and significant impact on wages for both male and female employees. The return to potential experience is higher for men than for women, especially for married men and married women. It contributes to gender wage inequality. Our data show that general working experience increases by one year will result in wage growth by 5.9% for men and 4.6% for women. This estimation is lower than what has been reported from other sources. The results indicate that general training for women does matter to narrow the gender wage gap. Moreover, when the career path is interrupted, such as by child care, the employee will suffer a substantial loss in wage growth. Specifically, in China, the 35-year-old threshold³ to labour market may exacerbate the gender wage gap for women.

Second, we found that there is no big difference in returns to experience and tenure between the overall male employees and the married male employees. Meanwhile, the return to the experience is much higher for the overall female sample than for the married female sample. This may be because getting married does not affect men's performance on the labour market, but usually negatively affects women, taking into consideration that women undertake more housework. Gender wage inequality could be clearly observed when comparing married male employees with married female employees. Our study confirms that returns to general experience for male and female employees are significantly different, which is the main source of the gender wage gap in China.

Table 7. Robustness test (cross section analysis with Heckman MLE).

	Men	Women	Chow-test	Married men	Married women	Chow-test
Test 1. Control for numbers of children						
Exp	0.027*** (0.005)	0.061*** (0.008)	11.585 [0.001]	0.016*** (0.006)	0.056*** (0.009)	12.596 [0.000]
Exp ²	-0.001*** (0.000)	-0.002*** (0.000)	14.704 [0.000]	-0.001*** (0.0001)	-0.002*** (0.0002)	14.857 [0.000]
Tenure	0.013*** (0.004)	0.011** (0.005)	0.046 [0.830]	0.014*** (0.004)	0.009* (0.005)	0.488 [0.485]
Tenure ²	-0.0001 (0.0001)	0.0001 (0.0002)	0.416 [0.519]	-0.0001 (0.0001)	0.0001 (0.0002)	0.968 [0.325]
Test 2. Use age as the proxy variable for experience						
Age	0.057*** (0.009)	0.103*** (0.015)	5.842 [0.016]	0.032*** (0.011)	0.098*** (0.018)	8.183 [0.004]
Age ²	-0.001*** (0.0001)	-0.002*** (0.0002)	6.725 [0.010]	-0.001*** (0.0001)	-0.002*** (0.0002)	8.551 [0.003]
Tenure	0.013*** (0.004)	0.014*** (0.005)	0.02 [0.888]	0.015*** (0.004)	0.012** (0.005)	0.236 [0.627]
Tenure ²	-0.00009 (0.0001)	-0.00004 (0.0002)	0.053 [0.818]	-0.0001 (0.0001)	0.00002 (0.0002)	0.414 [0.520]
Test 3. CFPS2012 cross section analysis						
Exp	0.029*** (0.006)	0.060*** (0.009)	8.046 [0.005]	0.020*** (0.006)	0.067*** (0.010)	13.957 [0.000]
Exp ²	-0.001*** (0.0001)	-0.002*** (0.0002)	6.836 [0.009]	-0.001*** (0.0001)	-0.002*** (0.0002)	11.423 [0.001]
Tenure	0.016*** (0.004)	0.020*** (0.006)	0.289 [0.591]	0.016*** (0.004)	0.017*** (0.006)	0.027 [0.869]
Tenure ²	-0.0002 (0.0001)	-0.0003 (0.0002)	0.133 [0.715]	-0.0002 (0.0001)	-0.0003 (0.0002)	0.046 [0.829]
Test 4. CFPS2014 cross section analysis						
Exp	0.033*** (0.004)	0.062*** (0.007)	10.653 [0.001]	0.011** (0.005)	0.066*** (0.008)	29.416 [0.000]
Exp ²	-0.001*** (0.0001)	-0.001*** (0.0002)	7.869 [0.005]	-0.000*** (0.0001)	-0.002*** (0.0002)	25.964 [0.000]

Notes: Only interested variables are listed in this table. Other controlled variables include: firm-type dummy (3), occupation dummy (6), industry dummy (19), and region dummy (24). There is no information on tenure in 2014 CFPS data, therefore tenure is not controlled for in test 4. ***, ** and * represent significance at the 1, 5, and 10% levels, respectively. Standard errors are in parentheses. *p*-Values are in brackets. Data source: 2010 CFPS data is applied in the cross section analysis. 2012-2014 CFPS data is applied in the panel analysis.

Third, our results indicate that compared with the return to general experience, firm-specific human capital contributes to a higher wage growth for both male and female employees. This may be because the delayed payment mechanism of wage determination and higher productivity resulted from specific training. This result is inconsistent with some previous studies (Abraham & Farber, 1987; Orłowski, 2010; Sulis, 2014; Strobl & Walsh, 1999; Williams, 1991), in which tenure has an insignificant influence on an individual's wage growth.

Finally, although the significance of coefficients is not technically reported in the Topel-2S model, there is no evidence of difference in the return to tenure between male and female employees when sample selection bias is corrected in the cross section model.

In sum, we conclude that return to experience is the main source of the gender wage gap, but return to tenure does not contribute to the gender wage difference. When comparing the return to tenure with that to general experience, the results indicate that the return to tenure is about 6% higher than that to the general experience for male employees and about 7–8% higher for female employees. In the area of

public policy, this result asks the government to provide more opportunities for professional training for female employees, specifically for married female employees.

The main limitation of this study is that we define tenure in a broader way. Some scholars (Goldsmith & Veum, 2002; Kambourov & Manovskii, 2009; Nawakitphaitoon, 2014; Neal, 1995; Parent, 2000; Sullivan, 2010; Zangelidis, 2008) argue that not just firm-specific human capital matters, industry-specific or occupational tenure may matter even more. The basic assumption for such arguments is that skills are transferable, thus the impact of firm-specific human capital on wage growth may be minor. It would provide more convincing results if we could define tenure in detail and explore the return to each of them under the MLE and Topel-2S models. This could be improved in future studies when rich data are available. Another extension of the study is to explore how much unemployment duration may ruin the increasing returns to general human capital and specific human capital. This will shed light on governmental policies on professional training and subsidies for female employees and unemployed employees.

Notes

1. Please refer to Fields and Yoo (2000) for a detailed discussion on this methodology.
2. Please refer to Oaxaca (1973), Blinder (1973), and Oaxaca and Ransom (1994) for a detailed discussion on the methodology.
3. In many employment advertisements, job candidates are required to be under 35 years old.

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References

- Abraham, C. G., & Farber, H. S. (1987). Job duration, seniority, and earnings. *American Economic Review*, 77(3), 278–297.
- Altonji, J. G. & Shakotko, R. A. (1987). Do Wages Rise with Job Seniority? *Review of Economic Studies*, 54, 437–459.
- Altonji, J., & Williams, N. (2005). Do wages rise with job seniority? A reassessment. *Industries and Labor Relations Review*, 58(3), 370–397.
- Antecol, H., & Bedard, K. (2004). The racial wage gap: the importance of labor force attachment differences across black, Mexican, and white men. *Journal of Human Resources*, 39(2), 564–583.
- Battisti, M. (2016). Individual wage growth: The role of industry experience. *Industrial Relations*, 55(1), 40–70.
- Becker, E., & Lindsay, C. M. (1994). Sex differences in tenure profiles: Effects of shared firm-specific investment. *Journal of Labor Economics*, 12(1), 98–118. doi:10.1086/298345

- Becker, G. S. (1975). *Human capital: A theoretical and empirical analysis, with special reference to education* (3rd ed.). Chicago, IL: The University of Chicago Press.
- Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources*, 8(4), 436–455. doi:10.2307/144855
- Bratsberg, B., & Terrell, D. (1998). Experience, tenure, and wage growth of young black and white men. *Journal of Human Resources*, 33(3), 658–682. doi:10.2307/146337
- Coleman, J. S. (1998). Do women earn higher returns to tenure than men? Evidence from the new earnings survey. *Applied Economics Letters*, 5(2), 65–68. doi:10.1080/758523505
- Cotton, J. (1988). On the decomposition of wage differentials. *Review of Economics & Statistics*, 70(2), 236.
- Dobbie, M., MacMillan, C., & Watson, L. (2014). The returns to general experience, job and occupational tenure: A study using Australian panel data. *Applied Economics*, 46(18), 2096–2017. doi:10.1080/00036846.2014.894632
- Dustmann, C., & Meghir, C. (2005). Wages, experience and seniority. *The Review of Economic Studies*, 72(1), 77–108. doi:10.1111/0034-6527.00325
- Fields, G. S., & Yoo, G. (2000). Falling labor income inequality in Korea's economic growth: Patterns and underlying causes. *Review of Income and Wealth*, 46(2), 139–159. doi:10.1111/j.1475-4991.2000.tb00952.x
- Gathmann, C., & Schonberg, U. (2010). How general is human capital? A task-based approach. *Journal of Labor Economics*, 28(1), 1–49. doi:10.1086/649786
- Goldsmith, H., & Veum, J. R. (2002). Wages and the composition of experience. *Southern Economic Journal*, 69(2), 429–433. doi:10.2307/1061681
- Guasch, J. L., & Weiss, A. (1982). An equilibrium analysis of wage-productivity gaps. *The Review of Economic Studies*, 49(4), 485–498. doi:10.2307/2297282
- Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1), 153–161.
- Hersch, J., & Reagan, P. (1990). Job match, tenure and wages paid by firms. *Economic Inquiry*, 28(3), 488–507. doi:10.1111/j.1465-7295.1990.tb01235.x
- Jann, B. (2008). A Stata implementation of the Blinder-Oaxaca decomposition. *The Stata Journal: Promoting Communications on Statistics and Stata*, 8(4), 453–479. doi:10.1177/1536867X0800800401
- Kambourov, G., & Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1), 63–115. doi:10.1111/j.1468-2354.2008.00524.x
- Lazear, E. P. (2009). Firm-specific human capital: a skill-weights approach. *Journal of Political Economy*, 117(5), 914–940.
- Light, A., & Ureta, M. (1995). Early-career work experience and gender wage differentials. *Journal of Labor Economics*, 13(1), 121–154. doi:10.1086/298370
- Munasinghe, L., Reif, T., & Henriques, A. (2008). Gender gap in wage returns to job tenure and experience. *Labour Economics*, 15(6), 1296–1316. doi:10.1016/j.labeco.2007.12.003
- Nawakitphaitoon, K. (2014). Occupational human capital and wages: The role of skills transferability across occupations. *Journal of Labor Research*, 35(1), 63–87. doi:10.1007/s12122-013-9172-2
- Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, 13(4), 653–677. doi:10.1086/298388
- Neumark, D. (1988). Employers' discriminatory behavior and the estimation of wage discrimination. *Journal of Human Resources*, 23(3), 279–295. doi:10.2307/145830
- Oaxaca, R. L. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14(3), 693–709. doi:10.2307/2525981
- Oaxaca, R. L., & Ransom, M. R. (1994). On discrimination and the decomposition of wage differentials. *Journal of Econometrics*, 61(1), 5–21. doi:10.1016/0304-4076(94)90074-4
- Orlowski, R. (2010). *Gender disparities in returns to tenure and experience*. Mimeo. Nuremberg: University of Erlangen-Nuremberg.

- Parent, D. (2000). Industry-specific capital and the wage profile: Evidence from the national longitudinal survey of youth and the panel study of income dynamics. *Journal of Labor Economics*, 18(2), 306–323. doi:10.1086/209960
- Regan, T. L., & Oaxaca, R. L. (2009). Work experience as a source of specification error in earnings models: Implications for gender wage decompositions. *Journal of Population Economics*, 22(2), 463–499. doi:10.1007/s00148-007-0180-5
- Reimers, C. W. (1983). Labor market discrimination against Hispanic and black men. *The Review of Economics and Statistics*, 65(4), 570–579. doi:10.2307/1935925
- Strobl, E. & Walsh, F. (1999) Do gender differences in returns to tenure matter anymore? *University College Dublin School of Economics*, working paper.
- Sulis, G. (2014). Wage returns to experience and tenure for young men in Italy. *Scottish Journal of Political Economy*, 61(5), 559–588. doi:10.1111/sjpe.12058
- Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. *Labour Economics*, 17(3), 567–580. doi:10.1016/j.labeco.2009.11.003
- The Global Gender Gap Report 2015. (2015). Switzerland: The World Economic Forum.
- The Green Book of Population and Labor 2016. (2016). China: Social Science Academic Press.
- Topel, R. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy*, 99(1), 145–176. doi:10.1086/261744
- Weiss, A. (1995). Human capital vs. signaling explanations of wages. *Journal of Economic Perspective*, 9(4), 133–154. doi:10.1257/jep.9.4.133
- Williams, N. (1991). Reexamining the wage, tenure and experience relationship. *The Review of Economics and Statistics*, 73(3), 512–517. doi:10.2307/2109577
- Williams, N. (2009). Seniority, experience, and wages in the UK. *Labour Economics*, 16(3), 272–283. doi:10.1016/j.labeco.2008.09.003
- Wooldridge, J. M. (2009). *Introductory econometrics: A modern approach*. Mason, OH: South-Western.
- Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics*, 30(1), 1–53. doi:10.1086/662066
- Zangelidis, A. (2008). Occupational and industry specificity of human capital in the British labour market. *Scottish Journal of Political Economy*, 55(4), 420–443. doi:10.1111/j.1467-9485.2008.00460.x