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Heterogeneous Returns to Education and Gender Wage Inequality in China: An IV-Quantile Regression Analysis

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Abstract

The paper explored the heterogeneous returns to education and gender wage inequality within wage dispersal in China by utilizing East Asian Social Survey (EASS) micro-level data from 2006 and 2016. Education is found to increase wages by about 7.2% on average, though the actual impact appears to be higher, around 15%, once underlying biases are considered. The returns remain fairly stable, between 7.2% and 7.5%, across most of the wage distribution. However, evidence shows clear heterogeneous returns to schooling rise from 12.2% at the 25th percentile to 15.7% at the 50th percentile, and further to 16.6% at the 75th percentile, indicating that individuals at higher wage levels benefit more from additional education. In terms of gender differences, results suggest a greater wage disparity at the lower end of the distribution, with men earning about 14.8% compared to 9.1% for women. The investigated study contributes unique visions by jointly observing both temporal and distributional magnitudes of educational returns in China, going beyond average effects. The implications recommend that while schooling stays to be a critical driver of wage growth, its paybacks are randomly dispersed and reinforce current disparities. Representatives should consider targeted interventions to balance labor market outcomes, especially for females.

JEL Codes: I26, J16, J31, O15

Keywords: Heterogeneous Returns, Gender Disparities, IVQR, Year Fixed Effect

Introduction

Education is an important element in the dynamics of contemporary employment markets. Several studies across various countries and historical periods have consistently indicated that individuals with higher education levels receive higher salaries, face lower unemployment rates, and hold more prestigious jobs compared to those with lower education (Card 1999). Likewise, Lucas (1988) viewed education return as a valuable currency in the area of human capital improvement, with endogenous growth models, notably augmented growth models, underscoring its pivotal role in influencing economic growth. The economics of education emerged in the early 1960's experiencing significant progress in subsequent eras. It distinguishes human capital from physical capital, acknowledging education as a distinct factor of production. Unlike physical capital alone, which is insufficient for driving economic development, education and skills serve as transformative elements in achieving economic goals in conjunction with physical capital.

Numerous studies support this notion, indicating that individuals with higher levels of schooling tend to earn higher wages, experience lower unemployment rates, and pursue more prestigious professions as compared to the less educated counterparts (Cooper & Cohn, 1997). Significant contribution to the field of education economics have made by influential figures such as (Schultz, 1961; Becker, 1964; Mincer, 1974). Their emphasis revolves around framing education as an investment in human capital rather than a mere cost. Schultz (1989) asserts that skills and knowledge acquired through education enhance an individual's productivity, resulting in a positive rate of return. Mincer (1974) adds to this perspective by positing that earnings follow a linear pattern with changing education levels and on the job training.

Frequent studies have shed light on education's role as a screening device. By imparting awareness, skills, and managing individuals toward suitable professions, education acts as a crucial screening mechanism. It serves as a foundational criterion for employers to gauge the fundamental assistances, abilities, and knowledge of individuals. Stiglitz (1975) underscores the significance of personal abilities in the context of firms, such as individual capabilities contributing to heightened productivity within a firm. The earnings is the dependent variable in our model, is the most crucial variable and also the determinant of employment sector achievements and fairness in society. The broader gap of earnings injustice or disparity in the state of China is very important to gain knowledge about earnings distinction, not only for legislators but also for educators and labor economist. Despite a significant rise in ordinary educational attainment, wage gaps have continued, moderately driven by differential returns to education. Furthermore, the earnings gaps constructed on sexual category and educational attainment highlight severe alarms regarding inclusive development. A crunch in earnings injustice is disrupting socio-economic development, in a people as large multipart as China's.

Although numerous studies have examined the educational returns in China (Churchill & Mishra, 2018; Mishra & Smyth, 2013; Kang et al., 2021; Ma & Iwasaki, 2021; Lin et al., 2025; Chen et al., 2020; Wang & Xu, 2022) absolute have either based on meta-analysis of heterogeneity returns to college graduates, rest of the studies focused on measuring educational returns between rural and urban respondents or pointed out endogeneity of schooling choices, these types of artless studies ignored the importance of heterogeneous educational returns at different levels of education. Furthermore, observe article uses reliable data from the East Asian Social Survey (EASS), a source rarely employed in empirical research. In response to the recognized research gap, this paper seeks to address key research questions. What are the educational returns among diverse quantiles of the wage dispersal? "To what extent does gender influence the returns to education in China''.

The objectives of this study are dual: to measure the heterogeneous returns to education across the wage distribution and to examine the connection between gender and education in determining wage inequality. Using two waves of the East Asian Social Survey (EASS), the study investigates how returns to education vary across different points of the earnings distribution and over time. While recent studies have explored rural and urban gender wage differences separately, this paper incorporates gender analysis within a broader scope, addressing important gaps in the existing literature. The rest of the study is organized as section 2, review of the literature, section 3, explanation of the research methodology and data sources, further the section 4, Results and discussion. Finally, section 5, which are related to conclusions and recommendations.

Literature Review

Before go on board the presentation about data and empirical results of the heterogeneous returns to education in China, it's mandatory to discuss historically and critically studies on returns to education and gender wage inequality. As the dominant study of Becker (1964) and Mincer (1974), the work on educational returns has developed a new discussion in the economics of education literature. To concern with Mincerian analysis and models several studies have measured educational returns in China. Numerous studies show that China's educational returns have risen over the past 21 years (Li, 2003; Li & Luo, 2004; Fleisher et al., 2011).

Initially, several studies suggested that educational returns have increased, but selected studies described findings contrary to these. When we investigated the data from 1986, we found that the educational returns were generally low, between 2.0-4.5%. By using mincer equations with OLS Byron and Manaloto (1990) indicated that the educational returns rate is 3.7%. likewise, Meng & Kidd (1997) also found the same trend of lower returns, 2.5% in 1981 and 2.7% for 1987 data. Maurer-Fazio (1999), Liu (1998), Knight & Lina (1991), and Gustafsson and Li (2000) analyzed data from the year 1981 using various database sources, such as the Chinese Household Income Project (CHIP) and the Urban Household Income Surveys, and found lower educational returns.

Various comparative studies of returns to education between the years 1988 and 1995 show evidence of higher educational returns in 1995 compared to 1988. Correspondingly, the study of Knight and Song (2003) using data from 1988 and 1995 concluded that the college graduates returns were 15.1% and 40.1% respectively. Thus, the study shows the lower returns to education in the 1980s data as compared to 1990's likewise, in 2000 data reported higher returns to education in people's republic of China (Heckman & Li, 2004; Li, 2003; Li et al., 2012; Mishra & Smyth, 2013). But it does not mean that, due to the data of updated time periods, returns to education are higher; rather, the returns are inconsistent. Similarly, the study on CHIP 2002 data Magnani & Zhu (2012) concluded by using the OLS model, the schooling returns for females are 4.2% and 4.1% for males. In my perspective, it is meaningful to measure the heterogeneous returns to education in the presence of inconsistency. Selected reviews of studies are associated with gender comparisons based on returns to education; the evidence suggests that the educational returns are higher for females than males (Zhang et al., 2005; Li and Ding, 2003; Maurer-Fazio, 1999; Magnani & Zhu, 2012). In distinction to these studies, the evidence of studies Chen & Hamori (2009) and Ren & Miller (2012) based on data Chinese Health and Nutrition Survey (CHNS) reported that the educational returns are to some extent greater than those of females.

Several studies compare educational returns across degree levels, plentiful studies showed that the higher degree returns are higher than lower rank. For example, Gustafsson & Li (2000) compared the 4-years college graduates and upper-middle-school the results are reported that returns of 4-years college graduates are higher than upper-middle-school education. Likewise, Chen and Hamori (2009) and Zhang and Zou (2001), estimated that the educational returns of college graduates are higher than lower education. Generally, these types of studies are strong evidence that higher education leads to higher returns. Fewer studies also exist in the presence of different age groups. For example, Liu (1998) reported that elder employees or additional knowledgeable employees have lower educational returns than newer or fresher employees.

Mu and Liu (2024) utilized 2019 household survey data and found that educational returns are higher for those people which are Mongolian names than for ethnic majority Han. Empirical results show that the college graduates who belong to Mongolian subject typically wage at 4,821.78 Yuan, as contrast with 4,509.32 Yuan for Han subject. likewise, in inner Mongolia, Mongolians which are highly educated they take care and relish of those policies which made for the minorities ethnic group (Jankowiak and Shurentana, 2016).

Model Specification

Jacob Mincer's wage model is a keystone in the field of economics of education or in labor economics, which was established in the 1970s. It's also the part the human capital theory, which was comprehensively explored by Jacob Mincer and Gary Becker. The main idea of this theory is that earnings of the respondents can be described through their accumulated human capital, which contains formal education and on work experience.

$$LogY_i = \beta_0 + \beta_1 Edu_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \epsilon \ldots\ldots\ldots\ldots\ldots\ldots \quad (01)$$

Furthermore, to estimate the gender wage inequality in this paper we are expanding the Mincer's and Becker's earnings model with explanatory variables Gender and year fixed effects, in equation 2, to allow the identification of changes in wage returns to education through time while holding constant undetected time specific stimulus.

So in this paper, the baseline model is finalized as:

$$LogY_i = \beta_0 + \beta_1 Edu_{it} + \beta_2 Exp_{it} + \beta_3 Exp_{it}^2 + \beta_4 Gen_{it} + \delta Year_t + \epsilon \ldots\ldots\ldots \quad (02)$$

Data Analysis

The paper is a quantitative style, by employing crossed sectional data from 2006 and 2016 from the East Asian Social Survey (EASS). Core motive of the article is to estimate the influence of heterogeneously returns to education or influence of years of China's education by adjusting other demographic variables via years fixed effects. EASS is the dataset of four partners Mainland China, Japan, South Korea and Taiwan. The objective of consideration two datasets is to expand the sample of the data and optimize statistical results, while fixed effects are used to adjust for year specific shockwaves.

This study focused on individuals aged between 18 and 65, presenting China's labor force population. Moreover, the last systematic sample is selected based on data comprehensiveness for key dependent and independent variables, including wages, years of education, gender, experience, and experience^2. Following Table 1 describes the variable's types and measurement.

Table 1: Variables their Types and Measurement

Variable	Type	Measurement
Wage	Dependent	Log of monthly wage (continuous)
Education	Target Variable	Years of education (continuous)
Gender	Independent	Dummy variable (0=Male, 1=Female)
Experience	Independent	Age in years (continuous)
Experience^2	Independent	Square of experience (Non-linear effects)
Dummy Year	Time effects	Dummy variable (1=2016, 0=2006)

Sources: Author's calculations.

The variable wage is calculated as the logarithm of the monthly wage of an individual in China and exists in local currency. Target variable "education" demonstrates the years of completed education by respondents. Further, gender is a dummy variable that includes both male and female. Other explanatory variables in the model are experience and experience^2 where we calculated experience by the method given by (Mincer, 1974).

$$Experience = (age - years\ of\ schooling - 6) \ldots\ldots\ldots\ldots\ldots \text{(03)}$$

The Mincer technique calculates work experience by subtracting years spent in schooling and the usual starting age for school (6) from the person's age. Experience^2, calculated by taking the square of experience, through this, we could analyses the experience and wage connection. Below Table 2, demonstrates the coefficient symbols and their relationship.

Table 2: Anticipated Coefficient Symbols and Theoretical Foundation

Variables	Expected Symbols	Theoretical Foundations
Education	Positive (+)	More education, higher wages
Gender	Negative (-)	Possibility of gender wage gap
Experience	Positive (+)	Imitates of accumulation in experience
Experience^2	Negative (-)	Diminishing Returns
2016	Uncertain	Net Effects (2006–2016)

Source: Author's calculations.

Estimation Techniques

Based on our specified model and given data, we are going to employ OLS, IVQR techniques to measure the heterogeneous educational returns in China with help of STATA. Quantile Regression (QR) is a statistical technique that prolongs outdated regression analysis by assessing the conditional quantiles of the response variable. Quantile regression is a useful method for modeling the effects of heterogeneous behaviors on consequence variables that are uncertain on covariates. The vector of $\beta(\theta)$ under the asymmetric least absolute deviation loss is defined as the θth regression quantile by (Koenker & Bassett, 1978).This problem can be effectively handled using convex linear programming.

$$\min_{b \epsilon R^K} \left[\sum_{t \in : yt > xtb} \theta |y_t - x_t b| + \sum_{t \in : yt > xtb} (1 - \theta) |y_t - x_t b| \right] \ldots\ldots\ldots\ldots \text{(04)}$$

In terms of interpretation, Hansen (2002) show that the outcomes could be expressed as follows in the latent outcome model, $Y\_d = (d, x, ud), u\_d \sim u(0,1)$ where the u_d is called rank variables and is responsible for heterogeneity in outcomes given covariates x and treatment status d. So the question is why we are not only relying on our baseline estimation technique? The answer is that Ordinary Least Squares (OLS) conventionally measures the ordinary outcome of independent variables on a dependent variable, supposing that differences through the conditional distribution are unimportant. On the other hand, this supposition may not hold, particularly when exogenous variables affect more than just the mean (Koenker & Bassett, 1978). To tackle this type of inadequacy, quantile regression (QR) captures all the effects of variables at different points of the outcome distribution. The human capital model, which relates earnings to education and experience, often simplifies returns by supposing identical special effects across people (Lemieux Firpo & Nicole, 2009).

To gain deeper visions that how education or years of schooling among different stages of wage, this paper employs quantile regression based on the Mincer (1974) earnings equation within the theoretical framework of Becker (1975). Furthermore, Instrumental Variable Quantile Regression (IVQR) is used to correct for endogeneity. So the

Instrumental Variable Quantile Regression (IVQR) provides a more suitable and nuanced results of how educational returns differ across wage distributions.

Empirical Analysis and Discussion

This section presents the empirical analysis and discussion of the study, focusing on the heterogeneous returns to education in China. Utilizing the Mincer-Becker model, the study empirically examines the relationship between education and monthly wages, incorporating supplementary variables such as experience, square of experience, and gender. The section is prearranged into different sectors. It initially demonstrates the descriptive statistics, then, employing the Ordinary Least Squares regression, shows marginal educational returns. Further, the section utilizes the updated estimation technique, Quantile Regression, which uses prolonged education of the mother as an instrumental variable for discussing potential endogeneity problems.

Later, we employed a simple QR and IVQR model which examines the varying returns to schooling among various wage quantiles. Gender dissimilarities are discovered in the instrumental variable quantile regression (IVQR) and Two-Stage Least Squares methods (2SLS). Lastly, the graphical representation of instrumental variable quantile regression (IVQR) results section includes visual assistance to demonstrate the results.

Table 3: Descriptive Statistics

Variables	Averages and SD	Sample Size
Log wage	10.104	N = 2667
	(0.878)	
Education	10.682	N = 2667
	(3.837)	
Experience	41.406	N = 2667
	(11.233)	
Experience^2	24.724	N = 2667
	(13.060)	
Female	0.420	N = 2667
	(0.494)	

Sources: Author’s calculations.

Table 3 presents key descriptive statistics from the East Asian Social Survey (EASS) datasets for China, covering the years 2006 and 2016. The average log wage is 10.104 (SD = 0.878), with an average of 10.682 years of education (SD = 3.837), and an average experience of 41.406 years (SD = 11.233). Experience^2 averages 24.724 years (SD = 13.060), and female mark up 42.0% of the sample (N = 2667).

Table 4: OLS and Robustness Regression: Educational Returns Overview

Variables	Model (1)	Model (2)	Model (3)
Education	0.099	0.095	0.072
	(0.004)***	(0.005)***	(0.015)***
Experience		0.004	0.062
		(0.004)*	(0.002)**
Experience^2		-0.001	-0.012
		(0.000)	(0.001)***
Female			-0.377
			(0.041)***
Year F.E.	No	No	YES
Constant	9.042	9.073	8.906
	(0.047)***	(0.092)***	(0.075)***

Observations	2,667	2,667	2,667
R-squared	0.189	0.190	0.464

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

OLS estimation results in Table 4, assessing the marginal returns to education in China, with the natural logarithm of monthly wages specified as the dependent variable in the model. The study presented three model specifications, each integrating a gradually richer set of controls to investigate the robustness of the predicted effects.

In model (1) coefficient of years of education is 0.99 (robust standard error=0.004), showing that every additional year of education is linked with an estimated 9.9% rise in monthly wages. This outcome is statistically noteworthy at the 1% level.

Model (2) prolongs the estimation by comprising prospective labor market work experience and its experience^2 term. The coefficient on education remains unwavering at 0.095 (robust standard error=0.005), keeping its high level of statistical significance. Experience comes in confidently 0.004 and is weakly significant, while the experience squared term is near to 0, suggesting a mild concave affiliation between experience and earnings. This pattern is consistent with the human capital theory, whereby early work experience contributes more extensively to earnings progress than later years. Model (3) presented the further explanatory variables results for males and females and integrates years fixed effects. In this comprehensively specified model, the coefficient on returns to education to some extent declines to 0.072(0.015), however, showing significance at the 1% endorsing the robustness of the projected educational returns, even after controlling for time trends and gender differences.

The inclusion of year fixed effects significantly improves the regression's explanatory power noticeably; R-squared increasing from 0.190 to 0.464, indicating that nearly half of the variation in wages is expressed by the model. Numerous studies indicated positive returns to years of education. For example, Zhao (2007) estimated OLS results of 6.3%, whereas Mishra and Smyth (2013) calculated returns of 10.8%. Further, Chen and Hamori (2009) found an average return of 8.02%.

The gender wage gap explained in Model (3) shows a significant wage disadvantage for females; the estimation results show that women earn approximately 37.7% less than men on average, adjusting for schooling and experience.

Quantile Regression Results Using Mother's Education as Instrumental Variable

We now extend our model by employing an instrumental variable quantile regression (IVQR), using the mother's education as an instrumental variable (IV) for monthly wages across China. A recent study by Winters (2015) Winters (2015) also utilized maternal education as an instrument to address endogeneity in wage estimations. The model further includes variables such as years of schooling, experience, experience squared, and gender, with robust standard errors applied.

Table 5: Marginal Returns to Education, IVQR Results

Variables	**Returns**
Education	0.150
	(0.015)***
Experience	0.011
	(0.004)**
Experience^2	-0.000
	(0.000)
Female	-0.150
	(0.027)***
Year F.E.	YES
Constant	7.882
	(0.208)***
First-stage	
Mother Schooling	0.239
	(0.015)***
Kleibergen-Paap rk LM statistic	205.980

P-value	0.000
Kleibergen-Paap rk Wald F statistic	262.052
Observations	2,623
R-squared	0.401

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 presented the coefficient of years of education is 0.150 (robust standard error = 0.015), significant at the level of 1% shows that additional years of education is connected with a 15.0% rise in monthly wages. These estimates are markedly higher than the corresponding ordinary least square estimates telling that ordinary least square could misjudge the true causal effect of schooling due to endogeneity rising from omitted variable bias or measurement error. The strength and power of the mother's education are sustained by the first stage values, where the coefficient of instrument is 0.239 (standard error = 0.015), and the Kleibergen-Paap rk Wald F-statistic is 262.052, faraway beyond conventional threshold of 10, confirming the instrument's relevancy and strength. Experience of work applies a positive and statistically significant result 0.011 (standard error = 0.004, $p < 0.05$), although its experience^2 is minor and insignificant, representing a weak or unimportant nonlinear connection. The female coefficient is -0.150 (standard error = 0.027), significant at the level of 1% indicating that females earn almost 15% lower than male respondents.

The presence of year fixed effects seizures time time-specific macroeconomic effects, and the model exhibits suitable explanatory supremacy, associated with an R-squared of 0.401. Generally, the instrumental variable quantile regression outcomes emphasize the robust and significant education returns and point out the importance of describing endogeneity to precisely measure the impact of education on wage.

Table 6: Heterogeneous Returns to Education, QR Results

Quantiles	**Q25**	**Q50**	**Q75**
Education	0.072	0.075	0.072
	(0.005)***	(0.007)***	(0.007)***
Constant	8.599	8,878	9.278
	(0.082)***	(0.115)***	(0.125)***
Observations	2,667	2,667	2,667
Pseudo R2	0.249	0.218	0.311

Note: Standard errors in parentheses. Control for experience, experience^2, gender, year Fe. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 6 explains the outcomes of quantile regression (QR) breakdown measurement of the impacts of education among the 25th, 50th, and 75th percentiles of the wage distribution in China. The returns to education at the 25th and 75th percentiles are estimated to be 0.072 and 0.075 at the 50th percentile, all statistically significant at the level of 1%. The results estimated that increase in wage, indicating the financial benefits of education are steady and homogeneously dispersed among different parts of the income distribution.

Furthermore, the years of education are found to gradually increase monthly wages, regardless of whether a respondent falls within the lower, middle, or upper segment of the wage distribution. The range of constant terms from 8.599 to 9.278, seizure baseline wage models for each quantile and all are statistically accurate. Pseudo R-squared estimated values range from 0.218 to 0.311, with higher descriptive supremacy at the 75th percentile, showing a suitable model fit for higher earners. If we compare estimated outcomes with earlier analyses of returns to education, such as the study by Leo (2012), it was shown that at the 50th percentile, the return to education is 3.49%, and at the 70th percentile, it is 4.52%. However, beyond this percentile, the returns slightly decline. Similar patterns were also reported in the studies of Wang et al. (2013). Furthermore, in the rural and urban study by Xing (2007), the returns follow a similar pattern, but at the 90th percentile, the returns become negative.

Table 7: Heterogeneous Returns to Education, IVQR Results

Quantiles	**Q25**	**Q50**	**Q75**
Education	0.122	0.157	0.166
	(0.005)***	(0.021)***	(0.016)***
Constant	7.893	7.786	7.978

	(0.328)***	(0.280)***	(0.226)***
Observations	2,623	2,623	2,623

Note: Standard errors in parentheses. Control for experience, experience^2, gender, year Fe. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 7 estimated the heterogeneous educational returns in China by utilizing instrumental variable quantile regression (IVQR). The assessment is calculated at the 25th, 50th, and 75th percentiles of the monthly wage dispersal.

The estimation shows that the returns to education increase among the wage dispersal, the coefficient on education years is 0.122 at the 25th percentile, 0.157 at the median, and 0.166 at the 75th percentile, all statistically significant at the 1% level. These findings suggest that an extra year of education raises monthly wages by roughly 12.2%, 15.7%, and 16.6% for lower, median and higher earner respectively. Thus this rising tendency suggests that education has a stronger effect on wages at higher quantiles, underlining its role in strengthening wage distribution. Furthermore, constant terms range from 7.786 to 7.978 are also statistically accurate, reflecting the baseline log-wage levels after regulatory for experience, experience^2, gender, and fixed year effects.

Table 8: Heterogeneous Returns to Education by Gender, IVQR Results

Male Returns		**Female Returns**	
2SLS	0.168	2SLS	0.133
	(0.022)***		(0.019)***
Q25	0.148	Q25	0.091
	(0.038)***		(0.021)***
Q50	0.171	Q50	0.135
	(0.033)***		(0.021)***
Q75	0.183	Q75	0.162
	(0.022)***		(0.022)***

Note: Standard errors in parentheses. Control for experience, experience^2, gender, year Fe. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 8 estimated the heterogeneous returns to education for gender by utilize Two Stage Least Squares (2SLS) and (IVQR) techniques. The estimation of the 2SLS shows that an extra year of education leads to an increase wage by 16.8% for males and for females 13.3% both estimations are statistically accurate at the level of 1%. This estimation is evidence that there is a gap in returns to schooling between males and females in the Chinese labor market.

Further in the next columns, there are the results of IVQR, which show how returns to education fluctuate among the monthly wage dispersion for gender, respectively. The estimation results explain that returns to education rise from 14.8% at the 25th percentile to 17.1% at the median and 18.3% at the 75th percentile. Whereas, for female respondents, estimation shows returns to education increasing from 9.1% at the 25th percentile to 13.5% at the median and 16.2% at the 75th percentile. So the measurement displays the increasing trend among different quantiles recommends that higher wage earner benefit more from extra education with the inconsistency in returns among gender being more noticeable at the lower end of the wage circulation.

This study is consistent with earlier research on the Chinese labor market. Gustafsson and Li (2000) founded that, even with the same characteristics respective to male, female schooling returns are lower than males. Correspondingly, Fan et al. (2015) provided evidence that urban females returns are lower than even highly educated while positive returns for rural male even less education. Li et al. (2024) investigated different sector like public, collective and private, findings of the study about public sector is that male earnings is 19.5% which are higher than female earnings, whereas 23.4% in the private sector, and a remarkable wage gap was in the collective sector, 38.1%. These findings are connected with our empirical results that females have continuously lower schooling returns across all wage levels.

Figure 1: IVQR Results: Graphical Representation of Heterogeneous Returns to Education

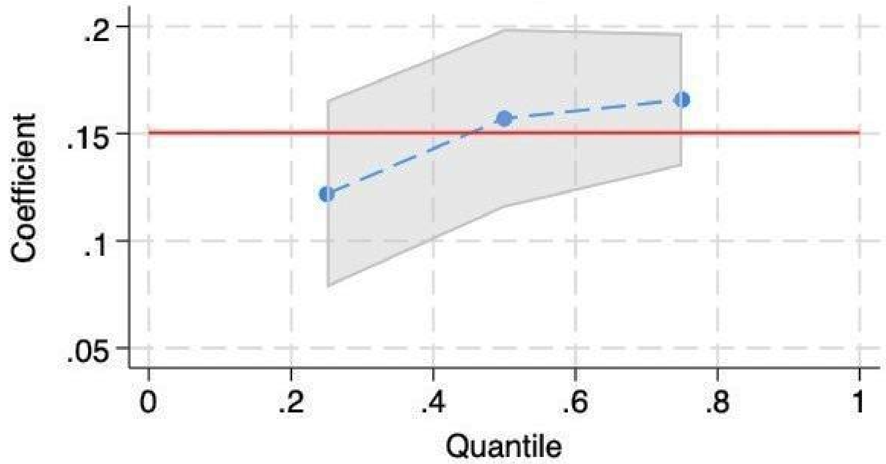
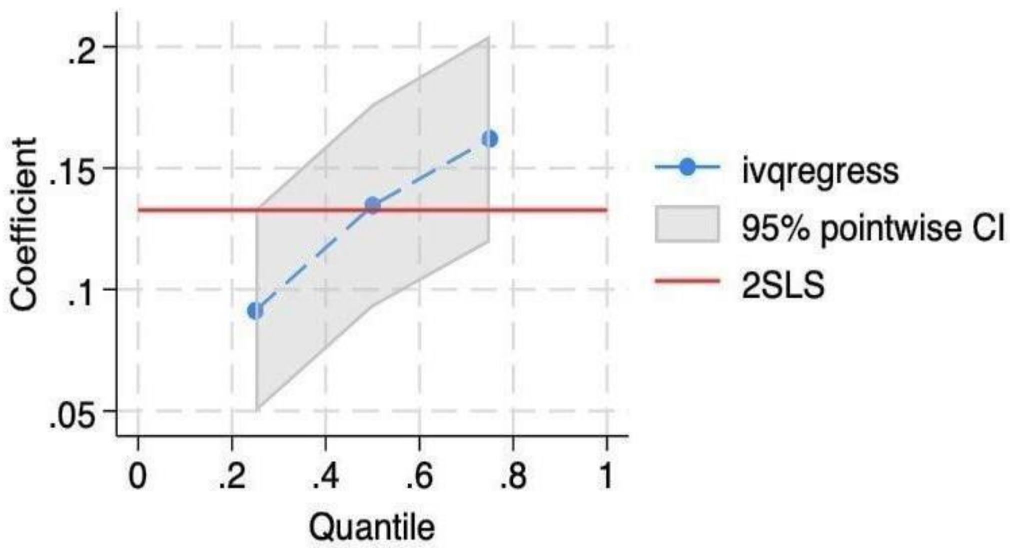


Figure 1 is the graphical representation of heterogeneous returns to education in China by employing the Instrumental Variable Quantile Regression (IVQR) method. In the graph, the x-axis demonstrates the monthly wage dispersal quantiles from 0.25 to 0.75, whereas, y-axis of the graph depicts the corresponding education coefficients. The blue lines show the point estimate at the quantiles 25th, 50th, and 75th, whereas the shaded area highlights the confidence intervals, and the red horizontal line illustrates the, average educational returns derivative from Two Stage Least Squares (2SLS) for assessment motive.

Further, when we look at figure 1, graphical values, it shows that returns to education are positive among all quantiles and rise smoothly from lower to higher quantiles, increasing from just above 0.12 at the 25th percentile to close to 0.17 at the 75th percentile. The increasing trend shows that respondents who belong to higher wage levels their returns are higher than lower wage earners. Further, the moderately narrow confidence bands recommend that the estimations are statistically accurate and robust.

Figure 2: Instrumental Variable QR Results for Female



The graphical representation in Figure 2, illustrates the instrumental variable quantile regression (IVQR) educational returns in China for females. The plotted values visibly show an increasing trend, which suggests that the educational returns for females increase from roughly 0.9 at the lower quantiles to about 0.14 to 0.17 at the higher quantiles. This trend shows that only education is fruitful for females as they move from lower to higher wage distribution, showing robust returns for higher earnings female respondents. Generally, the graph illustrates visual endorsement of heterogeneous educational returns and confirms the argument that education contributes to wage disparity even within gender clusters.

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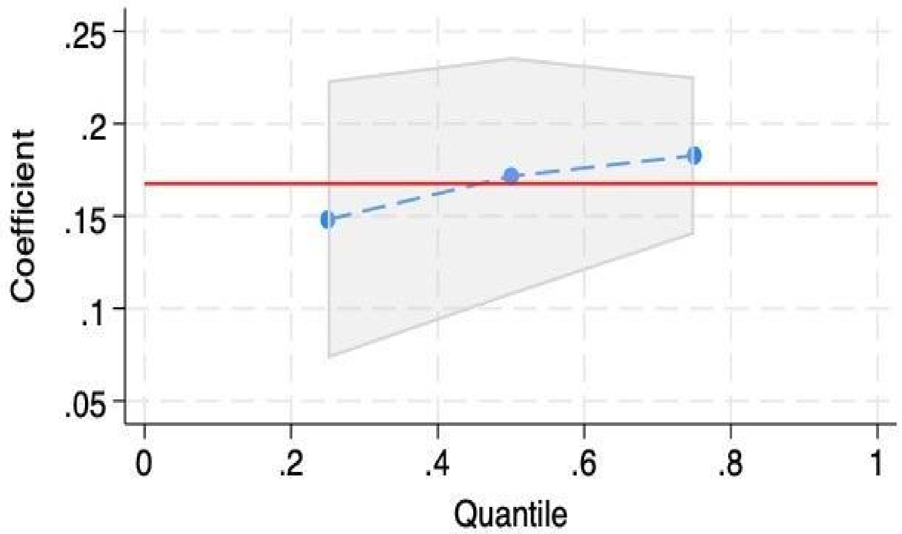
Figure 3: Instrumental Variable QR Results for Male



The plotted graph in Figure 3, explains the IVQR results of the educational returns for male respondents in China. We have been notified already about shaded areas, dashes, or red lines in recent graphs. Let us move to discuss the results of the coefficient at the 25th, 50th, and 75th quantiles. The plot shows the positive and, to some extent, ascending slope trend of the years of education returns rising from nearly 0.15 at the lower quantile to approximately 0.18 at the higher quantile. Thus, this increasing trend shows that the male workforce in the higher wage range earns slightly higher returns of additional education compared to those in the lower wage range. Thus, these estimates support the existence of heterogeneous returns across men in China.

Conclusion and Recommendation

The target of the study was to investigate the heterogeneous returns to education in China, utilizing cross-sectional data from 2006 and fixed effect data from 2016 of the East Asian Social Survey. Our theoretical background is Mincer-Becker; thus, we used Ordinary Least Squares (OLS), and Instrumental Variable Quantile Regression (IVQR) to measure the variations in returns among the wage dispersal and calculate gender gaps across the employment market in China. To address the endogeneity, the mother's education is used as an effective instrument.

The estimated results of the ordinary least squares statistically significant return of almost 9.9% per extra year of schooling. Afterwards, regulating experience, experience^2, gender, and fixed year effect returns a little drop to 7.2% but stayed significant. Further to address endogeneity, we employed IVQR, which showed that the return noticeably rose to 15%, indicating that the ordinary least squares miscalculate the causal effects of education on wages. The mother education instrument is valid and relevant, with a first-stage coefficient of 0.239 and a Kleibergen-Paap F-statistic beyond 260.

The simple QR results acclaimed the identical returns to education within wage dispersal, coefficient range from 7.2% to 7.5%. However, the instrumental variable quantile regression estimation shows increasing returns among different quantiles: 12.2%, 15.7% and 16.6% at the 25th, 50th, and 75th percentiles, respectively. These estimations denote that schooling yields greater payoffs for upper earners, gesturing the gaps in educational returns. Furthermore, we addressed the gender based analyses of returns, and we found that male respondents return more than female respondents. Male returns range is 14.8% to 18.3% whereas female returns range is 9.1% to 16.2%. The gender based gaps between males and females are higher at lower quantiles, which points out those females in lower-paying occupations face lower schooling payoffs, maybe due to the gaps in the employment market or occupational separation.

The paper concluded the robust proof of evidence of significant, in China's returns to education through the wage dispersal, with gender gaps. Discussing endogeneity proves that the old measurement of OLS underestimates these effects. Thus, schooling remains an influential but uneven tool for wage earners in the Chinese employment market. The estimation of the paper emphasizes human capital theory, challenging its homogeneity assumption. The upward returns associated with wage dispersal demonstrated that educational capital is more commendably in higher paying sections, associating heterogeneity in the returns structure. Furthermore, these estimates, also addition to the literature on gender based human capital returns; highlight the continuous wage inequality encountered by women.

The recommendation of the study is that Policymakers should prioritize equal access to quality education and skill-construction initiatives, mainly targeting low-income and female labor who earns lower returns. Employers of the institutions and human resource administrators must analyze pay fairness practices and offer wide-ranging training or skills courses to minimize gender inequalities. Educational curriculum should be aligned with labor force market demands to grow productivity and prime wages.

The paper enhances current confirmation in the provision of heterogeneous returns to education in China by utilizing nationally representative micro data from the 2006 and 2016 East Asian Social Survey (EASS). By employing mother education as an instrument variable and using IVQR, the research concludes causal and dispersal-complex schooling effects, emphasizing upward returns among the wage dispersal and gender-based disparity.

Firstly, the paper depends on cross-sectional data from 2006 and 2016 for year fixed effects, which might not reproduce the current labor employment framework. Secondly, unnoticed elements such as individual skill or occupational selections might still introduce bias. Thirdly, the utilization of mother education as an instrument variable, although statistically powerful, might not fully remove all endogeneity. Heterogeneity returns to schooling is an important and discussable topic for young researchers in such a populated and growing economy of the world. There are a lot of holes and research gaps that still exist to be filled. Future research could be based on different occupation, regions or between big and small cities of the Chinese labor market. Further research focuses on specific occupational data to check out the heterogeneity of returns to occupation.

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