# Estimating the Trend in the Returns to Education in China: Evidence from Longitudinal Data

Yifeng ZHANG

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**Abstract**

The returns to education in both developed and developing countries are well documented, but their changes over time remain under-researched. Using one of the most extended longitudinal datasets from China, we estimate the trend in the returns to education over the period 1993–2015. We found that returns to education in China have increased over time, with a significant rise from 2004. However, the results of the estimation also show a slight decrease from 2010 to 2015. We also find that the returns to higher educational degrees are high and have grown faster, especially for vocational degree education. Our findings are robust to different estimation methods, and the results are consistent with the literature.

**Keywords**: Longitudinal Data, Return to Years of Schooling, Educational Attainment, Human Capital, China

## 1. Introduction

The return to education is perhaps the most studied topic in the field of economics and education. Since the seminal work of Mincer (1974), previous research has documented a positive marginal monetary return of years of schooling. Psacharopoulos and Patrinos (2018: 449–450) have shown that the returns to education increased after 2000, compared to the pre–2000 period. Meanwhile, the evidence demonstrated that the global trend in over-time returns to schooling decreases by 0.2% for every additional year of education. This phenomenon may cause by the demand for skills is outpacing the growth of supply.

Recent evidence also suggests that the return to education in lower-and middle-income countries are experiencing higher estimates than higher-income countries, especially tertiary education. While most of the existing studies relied on cross-section data, questions have been raised about the credibility of these estimates for policymaking. For instance, Patrinos (2016: 278) points out the importance of considering the change in demand for education in estimating the returns to schooling. Therefore, this paper leverages one of the most extended longitudinal datasets for developing

countries to assess the extent to which the returns to education evolve over time.

As a crucial case for its large population, China has a fast-growing economy, stabilized society, and implemented policies. In 1986, the Compulsory Education Law of the People's Republic of China was launched from the education case. It firstly built up the foundation of education rights for every citizen. In order to adjust the education system more reasonably, the Compulsory Education Law had its first revision in 2006, the main idea is to balance the education resources in different areas, reduces the household burdens on education expenditures, and also expand the range of the definition on the students' learning objectives, which means not only basic knowledge are taught in the school but also the comprehensive abilities like physical, art, and manner education are required in the overall development. There is no doubt that a suitable and widely covered education structure is one of the keys to the country's long-term growth.

On the other hand, with the most acknowledged development over the past 40 years, people gradually accept new life patterns in China. There are already numerous studies on China's development and the different impacts of those essential investments from public and private. Since China's unique environment and policy implementation, it will be quite an experience for researchers to understand China's household education investment preference, the returns to education, and other related factors crucial to the individual outcomes. There are two specific objectives this study set out to investigate. First, we document the changes in the returns to education in China over a long period between 1993 and 2015. Second, we review critical government policies and external factors, and provide explanations on how they relate to the changes in the returns to education in China. These crucial factors are forging China's human capital development, requiring more empirical studies for better understanding and future planning.

To assess the trend of the return to education in China more accurately, a better understanding of China's achievement of the education sector should be one of the slightest requirements. Since the consistent education investment from the government and individuals poured into the education industry, the gross enrollment rate of primary school has been maintaining the level of 100% since 1990. The junior secondary school raised from less than 70% to 100% during the past 30 years. Besides China's compulsory school levels, senior secondary levels increased more than 60% of the gross enrollment rate to 80%. Concerning college degrees, a share beyond 40% of the gross enrollment ratio reflected a considerable leap from nearly zero starts in 1990. These incredible fast-growing enrollment rates in different education degrees were not useless. The share of illiterate people in every province in China declined sharply, even in the most rural area. (NBSC 2019)

The overall findings in this paper demonstrate an uprising trend in return to years of schooling, and educational attainment estimation in China starts from the early 1990s to the middle 2010s. There at least one continuous significant boost begun from the late 1990s and peaked in 2006. Although the estimates after 2011 show a slight decrease, it is still reasonable to admit the contribution of the

long-term education policy (These policies include, among others, the eighth curriculum reform for compulsory education period started from 1999 and public funds growth to stimulate the vocational educations before 2010.) as the returns to education are still very high compared to the early 2000s. The results in this paper are robust to different estimation methods, such as the Lewbel approach, a heteroskedasticity-based estimating method. Meanwhile, we measured the returns to education with varying dummy controls such as gender, works' type, and work units' type. We also show that the returns to higher educational attainment grew faster than fundamental education during the whole period, but vocational education became more popular after 2011.

The paper is organized as follows. Section 2 reviews the related literature on return to education, from both returns to years of schooling and educational attainment. In sections 3 and 4, the methodology and the data are explained as the basic structure of the estimation. Section 5 presents the estimate's major results, followed by the discussion on policy effect in section 6 and the conclusion in section 7.
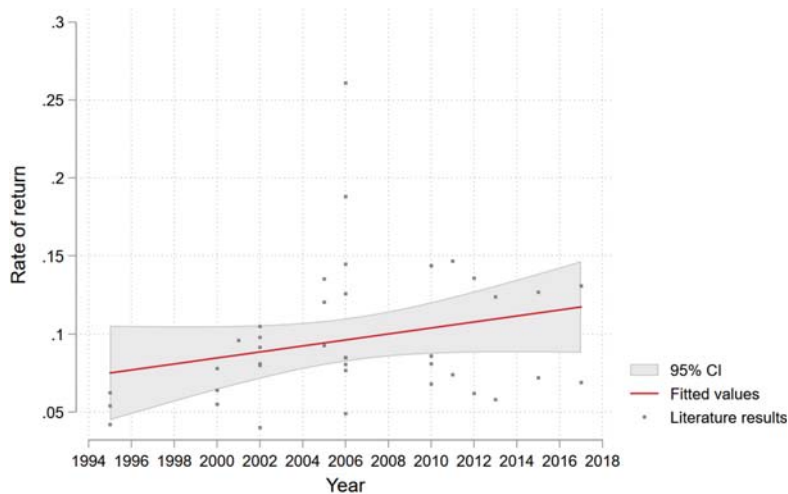
## 2. Literature Review

Human capital is a valuable capital that is costly to acquire and pays off over time, just like physical capital (Heckman 2005: 53–54). Within the considerable amount of the previous research, education is always one of the most critical factors. Literature generally has two kinds of major estimating approaches to quantify the education effect on human capital. One is the standard estimation of the return to years of schooling. This approach is implemented by a large number of papers with countless different datasets. On the other hand, literature also has quite some interests in the educational attainment influences. Due to the apparent and uprising features of different educational attainment, individuals should adequately have legitimate work.

Two measures have been generally used in the literature to assess the returns to education: years of schooling and the educational attainment. The year of schooling means the overall duration of one's education while educational attainment represents the highest degree an individual has obtained. First, we discuss previous studies on the returns to years of schooling. According to research based on 705 worldwide estimates, the private rate of return to an extra year of schooling was 8.8 percent from 1950 to 2014. The return to education is highest in Latin America and Sub-Saharan Africa, while the Middle East and North Africa get the lowest outcomes, according to Psacharopoulos and Patrinos (2018: 10). In China, the return to education has also been studied a lot in the literature. The mincer-type equation possibly covered most of the papers on this topic. They used various datasets and estimations methods to find out significant results in those years. We summarize the existing evidence to date on China's returns to education in Figure 1. These estimates were collected from 12 different studies published between 2003 and 2021. We can see that the overall trend of return to years of

education increases over time according to several different estimated results, just like the literature expected. In the 1990s, the return to years of schooling in China rose from at least 4% nationally (Xiu 2013: 235) to 5% (Kang and Peng 2010: 12). In the 2000s, these returns increased to more than 8% (Kang and Peng 2010: 12) on average. It can even reach a 14% level after 2010 (Chen and Pastore 2021: 15). However, Figure 1 also shows that the rates of the returns to educations years can be quite different even in the same year. This situation is mainly due to various datasets and methodologies.

**Figure 1　Estimated Rate of Return to Education Years in China from Literature**



Source: Estimated by the author based on the literature review.

Besides the literature which focuses on estimating return to the years of schooling, various studies have focused on educational attainment. We still start with the results from Psacharopoulos and Patrinos (2018: 11–12); their estimation shows higher education level may not necessarily bring better returns no matter it's a personal or social aspect. Furthermore, primary education always gives the highest return from low-income to high-income counties, and secondary or tertiary levels reflect similar results in the private sector. While social returns to the educational attainment are more appealed to primary level, and higher levels are giving lowest coefficient. They explain that higher education costs more increased investment, which hence the lower returns. However, they also believe that spending on human capital will continue to return as a good investment if utilized efficiently. The finding above is quite different from some other studies. From Melianova, Parandekar, and their colleagues (2020: 22–44), the return to the vocational degree is always lower than the university from 1994 to 2018. Also, the study focuses on China, like Fu and Ren (2010: 605) estimated in their work in the urban groups of the regression. Higher educational attainment did have higher returns.

These former studies on return to education have already given credits to education's inevitable

contribution. It is evident from the better-educated people that they have a better chance and can make better choices, both in traditional farming and those advanced jobs in the urban area (Yang 2004: 158). However, as one of the major economies and societies in Asia, the increase of the return to education in China was lower than other transitional economies, which means further development of China's return to education was expected (Chen and Hamori 2009: 151). Also, the return to education is not the same in the various sectors, and China's labor market has segmented views on wage determination (Xing 2008: 16). However, the age structure has been experiencing a population aging issue, which negatively affects human capital development (Fraumeni 2019: 865).

These results all remind us that even the overall return to education in China has gradually caught up with the average performance worldwide. Some external and internal issues are still troubling the dynamic balance between human capital performance and education investment. We believe further research is needed on China's case. It is essential to understand the actual status of the education's internal impact since each country's development won't necessarily share the same path. This paper would like to provide more support and clarify the understanding of China's human capital development on the education side.

## 3. Methodology

Our main objective is to estimate the returns to education using years of schooling and educational attainment over time. To do so, we first followed the literature and applied the mincer-type equation (Mincer 1974: 124) as the primary estimation method. Here, the return to education evaluation adopted the equation after Chen and Hamori's (2009: 146) procedure to fulfill the demand of this research process and restrict the same conditions. Our equation takes the form of

$$ln\ Y_i = aX_i' + \beta S_i + \varepsilon_i \tag{1}$$

where $\ln Y_i$ here represents the natural logarithm of the individuals' wage; $X_i$ denotes those factors that should be able to affect their wages, which include the age of the person and its quadratic forms (Age, Age squared), the gender, and work types; the education years of schooling is $S_i$ and $\beta$ will show the average rate of return to one more years of education; lastly, $\varepsilon_i$ is the error term with E $(\varepsilon_i) = 0$.

The OLS estimation with the Mincer-type equation has proved to be one of the methods in the research of return to education. However, we still need a double-check solution for the robustness issue of the original OLS results. Even this study would focus more on the general influence among all the factors. Commonly, instrument variables will be used to correct the effect of endogeneity issues. However, the difficulty of utilizing the instrumental variables method is finding the proper instruments that need the correlated relationship with the main factor and orthogonal to the whole approach's residuals. Such instrument variables may not be provided in the database. To solve this problem, Lewbel (2012: 68–69) developed a suitable way for estimating the impact on an outcome variable even

when the traditional instrument cannot be found.

The Lewbel approach can be described as follow:

$$Y_1 = X'\beta_1 + Y_2\,\gamma_1 + \varepsilon_1 \quad \varepsilon_1 = \alpha_1\,U + v_1 \tag{2}$$

$$Y_2 = X'\beta_2 + Y_1\,\gamma_2 + \varepsilon_2 \quad \varepsilon_2 = \alpha_2\,U + v_2 \tag{3}$$

$Y_1$ are wages, $Y_2$ is education, $U$ denotes the unobserved factors and $v_1$ and $v_2$ are the idiosyncratic errors. The whole approach will become convincing if the following conditions are achieved:

$$E\left(x_{\varepsilon j}\right) = 0, j = 1, 2 \tag{4}$$

$$\mathrm{cov}\,(Z, \varepsilon_1 \varepsilon_2) = 0 \tag{5}$$

According to Lewbel (2012), the identification is achieved by limiting the correlations of $\varepsilon\varepsilon'$ with X. The model will still be unidentified with standard homoskedasticity assumption, which means $E\left(x_{\varepsilon j}\right)$ is a constant matrix. The identification goal can be accomplished only if heteroskedasticity is related to some elements X to some extent. In an overall simultaneous structure, if $\mathrm{cov}\,(X, \varepsilon_j^2) = 0$, $j = 1, 2$ and *cov (Z, $\varepsilon_1\varepsilon_2$)* $= 0$ for observed Z, then it should be able to identify the structural parameters. Here the variable Z may be a subset of X, so no information outside the model specified above is required. However, if conditions (4) and (5) hold, together with heteroskedasticity of $\varepsilon_j$. The identification can be completed no matter Z is or isn't a sub-vector of X.

These conditions are standard assumptions for the test, and the only difference is that it requires heteroskedasticity in $\varepsilon$. The Lewbel approach can use traditional instruments with TSLS to estimate the IV regression like the conventional way (Mishra and Smyth 2015: 168-169). Furthermore, the initial test of Lewbel's approach showed a good result in Engle curve estimations, which is the household expenditure on a specific good or service varies with household income (Ernest Engel 1895), compared to the regular instrument variable approach using income. Support by this evidence, even if conventional IVs are not utilized or are not strong enough in the dataset, the Lewbel approach can efficiently provide consistent estimates.

Moreover, to estimate the returns to educational attainment, we use the following specification as in Otchia (2021: 6):

$$lnY_i = X_i'\gamma + \sum_{j=0}^{6}\beta_{ij}\,U_{ji} + \varepsilon_i. \tag{6}$$

Here, $U_{ji}$ represents the dummy variables of the highest level of education attained by individuals $i$ in each survey year. This specification assumes a non-linear function between education and earnings and allows us to estimate the returns to educational attainment from no formal education level to Master's and higher degrees. In addition, we can also evaluate the marginal effect of each education degree. The margins of each additional degree of educational attainment can reflect the return to education with more detailed results and offer over time changes of the human capital demand from society from the educational attainment distributions.

## 4. Data

The China Health and Nutrition Survey (CHNS) datasets are founded and collaborated between the Carolina Population Center at the University of North Carolina and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention (CCDC) internationally. It is one of the best datasets that can provide a most extended period of samples and is widely used in health, nutrition, and household planning policies, with comprehensive research. People can study the household level of Chinese society's transformation. The survey using a multistage, random cluster process within a 7–day period to draw the sample, including 7,200 households with over 30,000 individuals in 15 provinces and municipal cities. The datasets serve as longitudinal data, and its latest data was issued in 2015.

To demonstrate the return to education trend, this research utilizes eight waves of the CHNS data. These eight waves can provide a dynamic view of social improvement in China. In the 1990s, China took measures to popularize nine-year compulsory education thoroughly and eradicate illiteracy among young and middle-aged people, which is the foundation of rising human capital.

The selected data contains samples over 15 years old and under 70 years old within each period. We can understand the status by seeing statistics on the crucial variable in our datasets in 8 different years (Table 1). It is easy to observe the gradual increase of the samples' average annual wage and schooling experience. The data shows that the average age started from 36 in 1993 to 43 in 2015.

**Table 1   CHNS Data Description (1993 to 2015)**

| Variable | Year | 1993 | 1997 | 2000 | 2004 | 2006 | 2009 | 2011 | 2015 |
|---|---|---|---|---|---|---|---|---|---|
| Ln Wage | Mean | 7.542154 | 8.401392 | 8.671188 | 8.993186 | 8.846962 | 9.120834 | 9.637364 | 10.27063 |
| | S.d | 0.712715 | 0.705807 | 0.711163 | 0.75767 | 1.135138 | 1.324444 | 1.284494 | 1.064486 |
| Education Years | Mean | 6.711952 | 6.893084 | 7.485839 | 7.960441 | 8.128877 | 8.265542 | 9.06395 | 10 |
| | S.d | 3.957402 | 3.859649 | 3.749204 | 3.672412 | 3.971868 | 3.782317 | 3.974849 | 3.809596 |
| Age | Mean | 36.31075 | 37.39488 | 38.30178 | 42.02632 | 43.10831 | 43.8176 | 44.29166 | 43.98646 |
| | S.d | 12.74754 | 12.56562 | 12.40718 | 11.56723 | 11.23117 | 11.64613 | 11.43491 | 11.73799 |
| Gender | Mean | 1.469865 | 1.473911 | 1.460114 | 1.434289 | 1.435815 | 1.432402 | 1.444459 | 1.422282 |
| | S.d | 0.499126 | 0.499354 | 0.49844 | 0.495702 | 0.495903 | 0.495449 | 0.496937 | 0.49396 |
| Type of Work | Mean | 1.937241 | 1.933074 | 1.925771 | 1.920895 | 1.923941 | 1.914579 | 1.886614 | 1.885022 |
| | S.d | 0.242546 | 0.249912 | 0.262161 | 0.269924 | 0.265114 | 0.279529 | 0.317085 | 0.31902 |
| Type of Work Unit | Mean | 1.767072 | 1.772923 | 1.815576 | 2.308698 | 2.165436 | 2.122351 | 1.978092 | 1.621687 |
| | S.d | 0.558052 | 0.534037 | 0.555073 | 1.061561 | 1.015087 | 1.021746 | 1.038935 | 0.928705 |

Source: China Health and Nutrition Survey

Male (Male＝1, female＝2) maintains a more significant number than female in the samples during the whole period. We sorted two types of work (Knowledge-intensive work＝1 and Skill/Labor-intensive work＝2) according to the original 13 different categories from the CHNS datasets. Table 1 shows that more selected samples are Skill/Labor-intensive work, but the proportion of the Knowledge-intensive work slightly expanded over time. And four types of work unit type are also obtained (Government and public services＝1, State/Township/Province/City/County-owned enterprise＝2, Domestic private company＝3, and Enterprise owned by foreigners, overseas Chinese and joint venture＝4). We can find that state-owned enterprises may have accounted for a more significant ratio in the samples. To state it clearly, we are not focusing on geographic issues like household registration in this paper. The related variables won't be counted in the regression.

## 5. Results

Table 2 presents OLS estimates of the returns over 1993–2015. We find that positive and statistically significant estimates, implying the returns to education, have shown a positive trend over time. From a general view, the estimates generated by the OLS method demonstrate a similar trend to

**Table 2　OLS Result of the Return to Years of Schooling in China from 1993 to 2015**

| VAR. | 1993 Ln Wage | 1997 Ln Wage | 2000 Ln Wage | 2004 Ln Wage | 2006 Ln Wage | 2009 Ln Wage | 2011 Ln Wage | 2015 Ln Wage |
|---|---|---|---|---|---|---|---|---|
| Education Years | 0.014*** | 0.029*** | 0.046*** | 0.081*** | 0.097*** | 0.102*** | 0.122*** | 0.081*** |
| | (2.89) | (5.25) | (9.41) | (13.24) | (14.90) | (14.51) | (21.45) | (15.64) |
| Age | 0.056*** | 0.050*** | 0.038*** | 0.048*** | 0.076*** | 0.097*** | 0.118*** | 0.089*** |
| | (6.96) | (5.03) | (4.89) | (4.63) | (6.87) | (7.60) | (10.32) | (8.63) |
| Age-squared | −0.001*** | −0.001*** | −0.000*** | −0.001*** | −0.001*** | −0.001*** | −0.002*** | −0.001*** |
| | (−5.97) | (−4.25) | (−4.41) | (−4.42) | (−7.23) | (−8.24) | (−11.06) | (−9.50) |
| Gender | −0.139*** | −0.179*** | −0.150*** | −0.140*** | −0.258*** | −0.340*** | −0.308*** | −0.308*** |
| | (−5.63) | (−6.95) | (−5.89) | (−4.55) | (−7.27) | (−8.90) | (−10.91) | (−11.19) |
| Work Type | −0.071 | −0.001 | −0.185*** | −0.197*** | −0.438*** | −0.384*** | −0.310*** | −0.181*** |
| | (−1.57) | (−0.04) | (−4.43) | (−4.63) | (−8.97) | (−6.93) | (−7.32) | (−4.37) |
| Work Unit Type | −0.018 | 0.054* | −0.036 | −0.140*** | −0.246*** | −0.315*** | −0.236*** | −0.166*** |
| | (−0.59) | (1.83) | (−1.26) | (−5.68) | (−10.25) | (−10.98) | (−10.78) | (−7.10) |
| Constant | 6.620*** | 7.325*** | 8.082*** | 8.020*** | 8.279*** | 8.262*** | 7.813*** | 8.939*** |
| | (32.54) | (32.93) | (40.15) | (32.85) | (31.19) | (25.84) | (29.53) | (38.05) |
| Obs. | 2,748 | 2,448 | 2,573 | 2,224 | 3,232 | 3,521 | 4,953 | 4,751 |
| R-squared | 0.063 | 0.056 | 0.102 | 0.219 | 0.325 | 0.311 | 0.361 | 0.217 |

Note: *** p<0.01, ** p<0.05, * p<0.1
Source: Calculated by the author based on CHNS

the literature results.

Although the trend of returns to education years across these eight waves is overall increasing, it is worth noting that the estimates in the 1990s were lower than 3% and only 4.6% in 2000, and the returns after 2000 reached a whole new level. In 2006, 2009, and 2011, the return to the years of schooling maintained over the status around 10%. But the estimate in 2015 decreased back to the same level to 2004. These results match other research to the same degree. In detail, it is lower than the results, which we're focusing on urban China (Zhang, Zhao, Park, and Song 2005: 739) but close to the estimates using the same survey (Chen and Hamori 2009: 148). The R-Squares in the earlier waves are not very large but corroborate with preview literature which studied the returns to education on CHNS data (Chen and Harmori 2009: 148). Interestingly, we see significant variations in R-square across waves, meaning that our explanatory variables, including education, are becoming more important in explaining wage. Similar to Psacharopoulos and Patrinos (2018: 7), we also show that the returns to education years before 2000 were much lower than the world average but caught up with the same level after 2000.

On the other hand, the rest individual factors in the model are also showing the expected results. From the coefficients on age and age squared, potential earnings are higher with age growth. It started with 5% in the pre-2000 period and dropped to 3.8% in the year 2000. However, age has gradually increased and peaked at 11.8% in 2011 and slightly fell to 8.9% in 2015. Meanwhile, the Age2 (Age Squared) variable presents a negative coefficient through the estimation, meaning the marginal effect from the age to the wage decreases. In other words, the borderline relationship between age and wage is an inverted U curve. Individuals' salaries are growing through their lifetime, but the growth rate will rise at an early age and getting slower after a certain point. Males are still taking more advantage of females' workforces in job markets. The gap has been narrowed down after 2009, but 30% of the wage gap still stayed in front of females.

Although the individuals' work type only becomes significant after 2000, the trend still shows the fast growth of demand from the knowledge-intensive jobs and slow down its pace after 2006. From the macro view, the types of those samples' work unit variables have an odd trend that public services or non-private-owned enterprises seem to offer more wages after 2004.

The OLS estimation reveals that it almost tripled the return to education in China and maintained its level at 9% in the past 20 years. However, the marginal effect has shrunk quickly from 2011 (12.2%) to 2015 (8.1%). This trend is also suiting the findings from Asadullah and Xiao (2020). The possible reason for this decrease is that former boosted demand from the market reached a balance point, and the rate of return to education fell back to an average level. It can also explain the fact that the strategic policy initiative in China: "Supply-Chain Reform" and "Made-in-China 2025" Plan (Chen and Pastore 2021: 16). These visions should become the new engine of the market and society development and strengthen the demand for necessary education again at the same time.

To assess the robustness of these results, Table 3 presents the estimates from the Lewbel approach. We find that the returns to years of schooling estimated by Lewbel's approach are higher than the OLS method, which is constant with the literature such as Chen and Pastore (2021: 15), Mishra and Smyth (2015: 170). According to the original instrument variable method, the endogeneity issues could be caused by the selected conventional instrument. With the Hansen J test, we can see the whole period of its' P-value is over 0.05, which means the null hypothesis of the generated instrument variable is valid is accepted. Also, the Hansen J test result is consistent with the heteroskedasticity test, according to Hayashi (2000: 227-228, 407, 417). Since the robustness of the model provides substantial evidence, these factors' coefficients should be fair enough. In the trend, both methods show rapid growth in return to education after 2000 while OLS reflect the descendent after 2011 and Lewbel approach demonstrated the reversed U curve between 2006 and 2011. The estimates are more reasonable to the overall levels around the world, especially after 2000.

In Table 4, we expand our analysis of the returns to schooling by looking at educational attainment. Since we are interested in the heterogeneity in educational attainment, we provide results for the five degrees, with no education as the reference category. The only drawback is that our data does not include observation for master or higher education degree in 2004. Figure 2 only presents the marginal

**Table 3　Lewbel Approach Results of the Return to Years of Schooling from 1993 to 2015**

| VAR. | 1993 Ln Wage | 1997 Ln Wage | 2000 Ln Wage | 2004 Ln Wage | 2006 Ln Wage | 2009 Ln Wage | 2011 Ln Wage | 2015 Ln Wage |
|---|---|---|---|---|---|---|---|---|
| Education Years | 0.013 | 0.069*** | 0.052** | 0.117*** | 0.120** | 0.105** | 0.122*** | 0.122*** |
| | (1.55) | (3.24) | (2.22) | (2.87) | (2.37) | (2.36) | (6.08) | (4.22) |
| Age | 0.056*** | 0.044*** | 0.037*** | 0.044*** | 0.072*** | 0.096*** | 0.118*** | 0.085*** |
| | (9.42) | (5.07) | (6.12) | (4.42) | (7.08) | (6.22) | (8.40) | (8.15) |
| Age-squared | − 0.001*** | − 0.000*** | − 0.000*** | − 0.000*** | − 0.001*** | − 0.001*** | − 0.002*** | − 0.001*** |
| | (− 7.36) | (− 3.37) | (− 3.82) | (− 3.73) | (− 5.84) | (− 5.88) | (− 9.46) | (− 7.78) |
| Gender | − 0.140*** | − 0.171*** | − 0.149*** | − 0.135*** | − 0.242*** | − 0.339*** | − 0.308*** | − 0.301*** |
| | (− 4.91) | (− 7.77) | (− 3.62) | (− 5.57) | (− 6.03) | (− 5.01) | (− 5.27) | (− 5.16) |
| Work Type | − 0.074* | 0.095** | − 0.169** | − 0.100 | − 0.363* | − 0.374** | − 0.309*** | − 0.041 |
| | (− 1.77) | (2.21) | (− 2.40) | (− 0.74) | (− 1.77) | (− 2.25) | (− 2.88) | (− 0.37) |
| Work Unit Type | − 0.019 | 0.090*** | − 0.028 | − 0.123*** | − 0.231*** | − 0.313*** | − 0.235*** | − 0.160*** |
| | (− 0.97) | (2.59) | (− 1.04) | (− 3.71) | (− 5.00) | (− 4.40) | (− 3.27) | (− 3.37) |
| Constant | 6.635*** | 6.745*** | 7.977*** | 7.439*** | 7.881*** | 8.210*** | 7.805*** | 8.200*** |
| | (42.23) | (18.82) | (20.21) | (9.67) | (7.65) | (8.49) | (10.89) | (18.84) |
| Obs. | 2,748 | 2,448 | 2,573 | 2,224 | 3,232 | 3,521 | 4,953 | 4,751 |
| R-squared | 0.063 | 0.031 | 0.101 | 0.201 | 0.321 | 0.311 | 0.361 | 0.202 |
| Hansen J test | 0.196 | 0.357 | 0.159 | 0.0543 | 0.113 | 0.239 | 0.0501 | 0.105 |

Note: *** p<0.01, ** p<0.05, * p<0.1
Source: Calculated by the author based on CHNS

**Table 4　Return to Educational Attainment by Different Degrees**
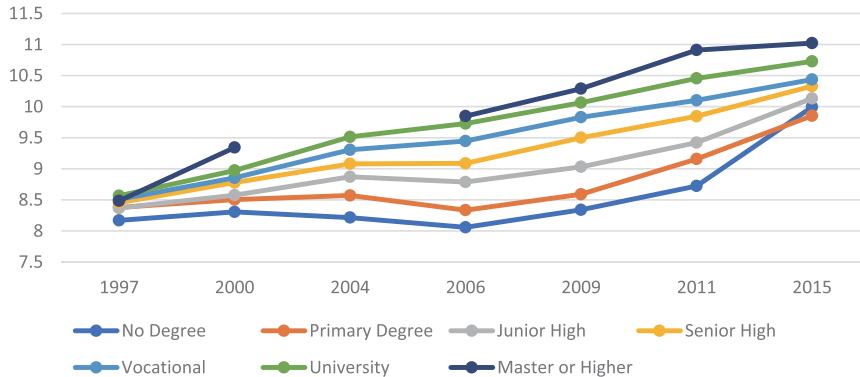
| VAR. | 1997 Ln Wage | 2000 Ln Wage | 2004 Ln Wage | 2006 Ln Wage | 2009 Ln Wage | 2011 Ln Wage | 2015 Ln Wage |
|---|---|---|---|---|---|---|---|
| Age | 0.048*** | 0.045*** | 0.042*** | 0.067*** | 0.112*** | 0.090*** | 0.070*** |
| | (4.60) | (4.82) | (3.34) | (4.60) | (7.19) | (6.53) | (5.48) |
| Age-squared | − 0.001*** | − 0.001*** | − 0.000*** | − 0.001*** | − 0.001*** | − 0.001*** | − 0.001*** |
| | (− 3.82) | (− 4.14) | (− 2.79) | (− 4.40) | (− 7.28) | (− 6.59) | (− 5.78) |
| Gender | − 0.183*** | − 0.172*** | − 0.162*** | − 0.299*** | − 0.436*** | − 0.334*** | − 0.318*** |
| | (− 7.60) | (− 7.45) | (− 5.12) | (− 7.99) | (− 10.59) | (− 11.69) | (− 11.32) |
| Primary Degree | 0.208** | 0.197*** | 0.356** | 0.276** | 0.249** | 0.434*** | − 0.140 |
| | (2.53) | (2.70) | (2.40) | (2.45) | (2.03) | (3.54) | (− 1.01) |
| Junior High | 0.198** | 0.271*** | 0.656*** | 0.729*** | 0.692*** | 0.697*** | 0.138 |
| | (2.51) | (4.05) | (4.60) | (7.10) | (6.05) | (6.12) | (1.10) |
| Senior High | 0.284*** | 0.472*** | 0.865*** | 1.028*** | 1.160*** | 1.122*** | 0.335*** |
| | (3.39) | (6.95) | (6.07) | (9.86) | (10.34) | (9.93) | (2.64) |
| Vocational | 0.339*** | 0.548*** | 1.092*** | 1.387*** | 1.489*** | 1.377*** | 0.441*** |
| | (3.89) | (7.73) | (7.66) | (13.59) | (13.49) | (12.09) | (3.45) |
| University | 0.396*** | 0.667*** | 1.298*** | 1.669*** | 1.725*** | 1.732*** | 0.734*** |
| | (4.30) | (9.04) | (8.91) | (15.76) | (15.58) | (15.64) | (5.92) |
| Master or Higher | 0.314 | 1.037*** | | 1.789*** | 1.949*** | 2.187*** | 1.029*** |
| | (0.87) | (3.67) | | (18.04) | (15.01) | (15.01) | (6.59) |
| Constant | 7.475*** | 7.663*** | 7.549*** | 7.230*** | 6.936*** | 7.584*** | 9.251*** |
| | (36.98) | (41.45) | (27.62) | (25.14) | (21.69) | (27.19) | (35.23) |
| Obs. | 2,704 | 3,007 | 2,173 | 3,041 | 3,275 | 4,671 | 4,387 |
| R-squared | 0.057 | 0.091 | 0.179 | 0.231 | 0.219 | 0.247 | 0.132 |

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Calculated by the author based on CHNS

effects of the education variables throughout the whole different eight years for straightforward interpretation. We find that the return of Masters' or higher degrees is gradually increasing each year but slows down in 2015. We see that only the returns to the primary school are tumbling during the sample years, and other degrees have experienced a constant growth from the pre-2000 period to 2011.

　The overall trend directly shows the uprising feature of the returns to educational attainment during the whole period, where primarily, vocational, university, and higher degrees maintained continuous ascending status. It's also clear that university and higher degrees of education have better returns on average. However, in secondary and lower degrees, their returns decreased in 2006. This phenomenon may be caused by the delayed impact of market demand for higher educated workforces.

**Figure 2　Education Margins to Ln Wage with Different Education Degrees**



Note: The original results table of Figure 2 is presented in the Appendix.
Source: Calculated by the author based on CHNS

Also, we could find that people could receive higher returns in wages after entering society if they sustained to upgrade the diploma. This finding is not solid with the international research by Psacharopoulos and Patrinos (2018: 454) but proved a similar result to the study from Fu and Ren (2010: 605). Unlike the return to education's decrease between 2011 and 2015, education degrees' margins seem experienced the reverted performance. In fundamental education degrees, people with no degree to secondary school degrees have better margins if they could upgrade one more level.

On the other hand, higher education like university and Master's degree graduates' returns rises less than those essential degrees. It reflected the situation that, although the return to education in the same period may drop because of the economic environment, fundamental education is still the necessary investment for most people. Even higher degrees couldn't bring as better margins as before. These typically educated individuals can generally still have higher margins than those who hold lower degrees. This result again affirmed the long-term return on the education investment and gave us a new way to understand the return to education's changing trend during the years.

## 6. Discussion

This study has demonstrated a positive trend in the returns to education using two indicators: years of schooling and educational attainment. However, several aspects of our findings need discussion. As a complex and continuously evolving society, China needs a modernized and demand-driven education system to develop different areas accurately. First, we found that the returns to education are not stable in recent years. Several reasons triggered this fast boost of returns to education, given that the coefficient almost tripled from 2000 to 2011. From the supply side, the Chinese government created many incentives to strengthen education policy and delivery. As early as 2002, China introduced a social market education institution intending to decentralize decision-making (budget, curriculum,

etc.) and increase the privatization of public schools (Fan and Popkewitz 2020). For instance, China introduced the eighth wave of curriculum reform in 1999. Unlike the former curriculum reforms, this eighth wave rebuilt China's education system from the basic concept. Students can receive a more balanced and flexible learning style that aims to understand how to learn and keep a positive attitude. The eighth wave of curriculum reform came up with a better and positive relationship between student and teacher and developed innovative approaches to the education system (Cui and Zhu 2014: 2). It also reduces the mismatch between the education system and labor market demand with better education quality. Another essential factor is government expenditure on education, which increased to address the quality of education. Existing data show that public expenditure increased from 2.56% of GDP in 2000 to 4.28% in 2012. And the most direct effect is that the student-teacher ratio has a different trend in each degree after 2005. It first appears at primary and secondary school levels, which means more teachers are available in the fundamental education system. Vocational degrees student-teacher ratio increased before 2010 and sharply decreased right after. From the college part, it remained at the level of 17 and slightly increased after 2007. These trends match the return to educational attainment results and support the explanation of the improving education quality (NBSC 2019).

From the demand side, explanations could also be derived from the growth in the market demand of skills as partially illustrated in our findings on the returns to educational attainment. The gradually opened market and a positively developing social environment generally demand higher educated labor in China. In the meantime, China's industrialization, alongside the reform strategy, introduced foreign direct investment from all over the world. Under these circumstances, both the service sector and industry were in great demand for post-secondary degree graduates in the late 1990s and early 2000s (Ding, Yang, and Wei 2013: 391–393). The market demand for qualified personnel by different kinds of enterprises and manufacturing and technology sectors projected the benefit to the need of the education, which also promoted the return to education growth in the estimation after China participated in WTO in 2001 (Ding, Yue, and Sun 2009).

Second, we also sound that the trend in the returns to education weakened after 2011. Several hypotheses may explain this decline. One of the possible reasons is that the high expansion of the demand for highly educated labor in quantity costs the general quality decline of the graduates (Asadullah and Xiao 2020: 16). Another reason might be the structural change of the industry. China launched several innovation-oriented policies after 2010, aiming to strengthen the comprehensive ability in the domestic industries as the other growth engine (Zilibotti 2017). These strategic changes firmly pushed China's domestic market and may take responsibility for the structural mismatch to the former education target.

Taken together, our findings are consistent with former studies in the literature. Lewbel estimates indicated the significant results with a generated IV in the model (Mishra and Smyth 2015: 172). The

sharp increase of the returns to education since the 1990s driven by economic reform is similar to other transition economies (Zhang, Zhao, Park, and Song 2005: 748). Gender inequalities still exist as for wage gap is getting more significant over time. Knowledge-intensive works are more popular than skill-intensive works, but due to the structural changes, skill-intensive jobs may receive higher expectations in future development. Public services seemed continuous to be a better choice for the graduates since China has its unique hybrid economic system. But through the trend, perhaps an open market will offer more opportunity to the private sector because the educational attainment margins suggest that the market still welcomes those who hold a higher education diploma. However, more structural demand pointed to vocational education.

## 7. Conclusions

This study, as we designed, aims to demonstrate the trend of returns to education in China in the past two decades. By utilizing the CHNS longitudinal data with Mincer and Lewbel approach, we estimate the return to years of schooling and educational attainment, respectively. Since former studies on returns to education in China in the literature focused on one or two specific years or generated results on-trend but did not simultaneously estimate returns to education years and attainment. This study is well-fitted in the literature and carrying out several solid conclusions.

On the one hand, the overall trend shows that the eighth curriculum reform significantly upgraded return to years of schooling in the 2000s. The market demand was also gradually fulfilled by the quality-improved educational attainment. On the other hand, controlled variables on gender, work issues, and estimation of educational attainment margins reflected that external and internal impacts to human capital development in China constantly exist.

Externally, we observed the influence of the gender gap issues, which are still generating inequality problems. We also see the private sector market and large companies' advantages and market preference on the knowledge-intensive labors. The internal impact uncovered by education margins shows the positive trends during educational attainment growth. We see improvements in higher education that generate more margins on wages and more opportunities and acceptance to the vocational degrees offered by the fast-developing market. Although long-term returns to education may not remain the same in the future, the positive effect of sustainable education investment from various sources shouldn't be ignored.

We realize that human capital development in China needs more comprehensive studies like education investment distribution and health factors. Our future study will focus on provincial-level human capital research by estimating education policy, health issues, and economic influences. These perspectives will help us understand and project future macro policy development in China from the human capital side.

# Acknowledgment

## References

Asadullah, M. Niaz; and Xiao Saizi. 2020. The Changing Pattern of Wage Returns to Education In Post-Reform China. *Structural Change and Economic Dynamics.* 53: 137–148.

Chen, Guifu; and Shigeyuki Hamori. 2009. Economic Returns to Schooling in Urban China: OLS and the Instrumental Variables Approach. *China Economic Review.* 20 (2): 143–152.

Chen, Jie; and Pastore Francesco. 2021. "Study Hard and Make Progress Every Day": Updates on Returns to Education in China. *GLO Discussion Paper Series.* No: 787.

Chow, Gregory C.; and Shen Yan. 2006. Demand for Education in China. *International Economic Journal.* 20 (2): 129–147.

Churchill, S. A.; and Mishra, V. 2018. Returns to Education in China: A Meta-Analysis. Applied Economics. 50 (54): 5903–5919.

Cui, Yunhuo; and Zhu Y. 2014. Curriculum Reforms in China: History and the Present Day. *Revue internationale d'éducation de Sèvres.*

Ding, X., Yang S.; and Wei H. 2013. Trends in the Mincerian Rates of Return to Education in Urban China: 1989–2009. *Frontiers of Education in China.* 8 (3): 378–397.

Ding, X., Yue C.; and Sun Y. 2009. The Influence of China's Entry into the WTO on Its Education System. *European Journal of Education.* 44: 9–19.

Engel, E. 1895. Die Lebenskosten belgischer Arbeiter-Familien fruher und jetzt. *International Statistical Institute Bulletin.* 9 (1895): 1–74.

Fan, Guorui; and Thomas S. Popkewitz. 2020. *Handbook of Education Policy Studies.* Singapore: Springer Nature.

Fan, Wen, Ma Yuanyuan; and Wang Liming. 2015. Estimating the External Returns to Education: Evidence from China. *IZA Discussion Papers.* No: 9133.

Fraumeni, B. M., He J., Li H.; and Liu Q. 2019. Regional Distribution and Dynamics of Human Capital in China 1985–2014. *Journal of Comparative Economics.* 47 (4): 853–866.

Fu, Qiang; and Ren Qiang. 2010. Educational Inequality Under China's Rural-Urban Divide: The Hukou System and Return to Education. *Environment and Planning A.* 42 (3): 592–610.

Hayashi, F. 2000. *Econometrics.* Princeton: Princeton University Press.

Heckman, J. 2005. China's Human Capital Investment. *China Economic Review.* 16 (1): 50–70.

Hu, Feng. 2015. Return to Education for China's Return Migrant Entrepreneurs. *World Development.* 72: 296–307.

Kang, Lili; and Peng Fei. 2010. Education Return in Urban China: Evidences from CHNS Dataset. *The Chinese Economic Association (UK) 2010 Annual Conference and 2nd CEA (Europe) Annual Conference.*

Lewbel, Arthur. 2012. Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models. *Journal of Business and Economic Statistics.* 30 (1): 67−80.

Melianova, E., Parandekar, S., Patrinos, H. A.; and Volgin, A. 2020. Returns to Education in the Russian Federation: Some New Estimates. *IZA Discussion Paper.* No: 13726.

Mincer, Jacob. 1974. *Schooling, Experience and Earnings.* New York: NBER.

Mishra, Vinod; and Russell Smyth. 2015. Estimating Returns to Schooling in Urban China Using Conventional and Heteroskedasticity-based Instruments. *Economic Modelling.* 47: 166−173.

National Bureau of Statistics of China. 2019. *China Statistical Yearbook.* Beijing: China Statistics Press.

Otchia, C. S. 2021. Returns to Educational Attainment in Urban Ghana: The Role of Job-to-Job Transition. *Progress in Development Studies.* 21 (1): 51−67.

Patrinos, Harry Anthony. 2016. Estimating the Return to Schooling Using the Mincer Equation. *Iza World of Labor.*

Psacharopoulos, George; and Harry Antony Patrinos. 2018. Returns to Investment in Education: A Decennial Review of the Global Literature. *Education Economics.* 26 (5): 445−458.

Qian, Xiaolei; and Russell Smyth. 2008. Private Returns to Investment in Education: an Empirical Study of Urban China. *Post Communist Economies.* 20 (4): 483−501.

Wang, X., Fleisher, B. M., Li, H.; and Li, S. 2014. Access to College and Heterogeneous Returns to Education in China. *Economics of Education Review.* 42: 78−92.

Xing, Chunbing. 2008. Human Capital and Wage Determination in Different Ownerships, 1989−1997. *Wider Working Paper.* 2006 (121).

Xiu, L.; and Gunderson, M. 2013. Credential Effects and the Returns to Education in China. *Labour.* 27 (2): 225−248.

Yang, Dennis Tao. 2004. Education and Allocative Efficiency: Household Income Growth During Rural Reforms in China. *Journal of Development Economics.* 74 (1): 137−162.

Zhang, J., Zhao, Y., Park, A.; and Song, X. 2005. Economic Returns to Schooling in Urban China, 1988 to 2001. *Journal of Comparative Economics.* 33 (4): 730−752.

Zilibotti, Fabrizio. 2017. Growing and Slowing Down Like China. *Journal of the European Economic Association.* 15 (5): 943−988.

# Appendix

### Table 7　Education Margins by Different Degrees

| VAR. | 1997 Ln Wage | 2000 Ln Wage | 2004 Ln Wage | 2006 Ln Wage | 2009 Ln Wage | 2011 Ln Wage | 2015 Ln Wage |
|---|---|---|---|---|---|---|---|
| No Degree | 8.170*** (104.37) | 8.306*** (130.79) | 8.215*** (59.11) | 8.058*** (84.11) | 8.340*** (80.82) | 8.723*** (80.86) | 9.994*** (81.60) |
| Primary Degree | 8.378*** (231.39) | 8.503*** (218.86) | 8.571*** (163.73) | 8.334*** (115.97) | 8.589*** (116.97) | 9.157*** (148.87) | 9.854*** (151.81) |
| Junior High | 8.369*** (345.13) | 8.576*** (366.29) | 8.871*** (268.58) | 8.787*** (240.35) | 9.032*** (205.72) | 9.421*** (248.95) | 10.132*** (346.67) |
| Senior High | 8.454*** (311.00) | 8.778*** (324.15) | 9.080*** (261.10) | 9.087*** (222.80) | 9.500*** (213.71) | 9.845*** (284.13) | 10.330*** (277.69) |
| Vocational | 8.509*** (221.56) | 8.854*** (272.58) | 9.306*** (292.20) | 9.446*** (300.80) | 9.829*** (255.63) | 10.101*** (275.71) | 10.436*** (297.16) |
| University | 8.566*** (176.99) | 8.973*** (233.66) | 9.513*** (220.91) | 9.728*** (227.00) | 10.065*** (267.71) | 10.455*** (439.84) | 10.729*** (425.71) |
| Master or Higher Degree | 8.484*** (24.05) | 9.342*** (33.88) | | 9.848*** (412.59) | 10.289*** (130.53) | 10.911*** (112.32) | 11.023*** (114.01) |
| Obs. | 2,704 | 3,007 | 2,173 | 3,041 | 3,275 | 4,671 | 4,387 |

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Calculated by the author based on CHNS