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Who Gets the Highest Return to Distance Higher Education?

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See table of contents

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Article abstract

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Who Gets the Highest Return to Distance Higher Education?

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Abstract

The economics of distance higher education have not attracted enough attention. Few studies have analyzed the different returns to distance higher education at various income levels. Based on empirical analysis of data from China Family Panel Studies (CFPS), this study explored the differences of return to distance higher education at different income levels by using Mincer earnings function and quantile regression. Compared with face-to-face education, the study found that distance higher education brought considerable benefits to learners. While the return to face-to-face higher education has continued to decline, return to distance higher education has risen. Comparing the returns to distance education at different income levels showed that low-income groups obtained greater benefits from distance higher education, which can help to improve the income of vulnerable groups and promote social equality. China's distance education institutions should promote the idea that distance higher education can improve the income growth of low-income groups, and increase the financial support for low-income groups to access distance higher education.

Keywords: distance higher education, return to education, quantile regression, low-income group

Introduction

Distance higher education has a long history, and students all over the world have received education at a distance. In 2013, there were more than 21 million distance education learners in developing countries alone (Bates, 2013). In China, for example, every year, nearly one million students have received nationally recognized junior college and university degrees through distance higher education. In 2019, there were about 2.32 million undergraduate and junior college graduates of online education in China, which accounted for 19.30% of the total number of universities and college graduates that year.[1] Since much adult education is available via distance education, with online learning just one part of the whole, the proportion of graduates of distance higher education in China far exceeded the 19.30% that was online. Even though the scale of distance education in Chine is large, it has long been underestimated by the public.

The rate of return to education is an important indicator for evaluating the economic value of education at different levels, in various categories, and for a range of academic majors. In turn, studies on return to education can promote the development of education (Psacharopoulos & Patrinos, 2004). Many studies have focused on return to conventional face-to-face education. For example, the 2021 Nobel Prize in Economic Sciences recognized the prominent contribution of three experts—Joshua Angrist, David Card, and Guido Imbens—who accurately evaluated the rate of return to education (National Bureau of Economic Research, 2021).

Most studies on return to education have focused on face-to-face education; a few have looked at return to distance education (Li & Wang, 2021). In many countries, distance education has been seen as subordinate and low-quality education (Chen & Wang, 2010; Gaskell & Mills, 2014). The lack of research in this field may lead to seriously underestimating the return to distance education, and ignoring the development of distance education, leading to a cycle of negative feedback regarding distance education. Since the outbreak of the global COVID-19 pandemic, distance higher education has attracted wider public attention and discussion.

Psacharopoulos (1985, 1994) compared the returns to higher education in different countries. In the countries from the Organization for Economic Cooperation and Development, as a representative of high-income countries, the return to higher education was 12.3%, and in upper-middle-income countries, the rate was 14.8%. Is the phenomena of return to higher education in high-income countries being lower than in upper-middle-income countries applicable to distance higher education?

Based on previous research, this study explored the differences of return to distance higher education at various income levels to identify which group obtained the higher return by using quantile regression and representative household survey data in China. This study sought to fill a gap in the literature and advise distance education institutions on ways to reduce income inequality.

Literature Review

Return to Face-to-Face Higher Education

Since the emergence of human capital theory in the 1960s, empirical research on return to education has attracted considerable attention (Carnoy, 1995; Heckman et al., 2006; Johnes et al., 2017). The research on return to higher education has mainly focused on two aspects of face-to-face education—measuring return to higher education and the differences of return to higher education among various groups.

Previous studies mainly focused on the differences of return to face-to-face higher education for (a) different genders, (b) urban and rural areas, (c) different regions, (d) different sectors, and (e) different disciplines. Regarding urban and rural areas, most research showed that the return to education was higher for urban areas than rural (Johnson & Chow, 1997; Liu & Liu, 2020; Zhang & Jin, 2020). Most analysis of the differences among regions showed that the return to education was higher in developed regions in east China than western underdeveloped areas (Li, 2017; Shen & Zhang, 2015). Overall, face-to-face higher education in economically developed regions has had higher returns.

Return to Distance Higher Education

Little research has focused on the measurement and comparison of distance higher education. Woodley and Simpson (2001) measured the return to investment in distance higher education and found that the return for graduates of distance higher education was higher than average. Carnoy et al. (2012) compared the return to distance higher education in terms of different degrees and academic majors. Some scholars have found that the investment in distance higher education was not worthwhile, since the return was relatively low (Hoxby, 2017).

Compared with other countries and regions, there have been more studies on the return to distance higher education in China. Zheng et al. (2009) calculated the individual return to distance higher education in a network college of a university compared to return to education in different disciplines. Li and his collaborators conducted a constant study on the return to distance higher education (Li, 2018; Li, Li, & Zhang, 2015; Li & Wang, 2020; Li & Wang, 2021). Based on the analysis of samples from Radio and TV University of China and the representative samples of the country, they compared the returns between distance higher education and face-to-face higher education. They also compared the differences of return to distance higher education in terms of (a) changing trends, (b) genders, (c) urban and rural areas, and (d) different disciplines. Studies of the labor market in China have verified that distance higher education brought considerable individual returns for learners, which is consistent with Carnoy et al. (2012) and Castaño-Muñoz et al. (2016).

Literature Review in Summary

Previous studies have mainly used quantitative methods to explore the return to distance higher education. Qualitative methods have been used to analyze the issues of distance learners or the quality of distance education (Esfijani, 2018; Yang & Cornelius, 2004). So far, no empirical analysis has been made on the differences of return to education among different income groups of distance higher education graduates.

Abdullah et al. (2015) and Qazi et al. (2018) pointed out that education was particularly effective in reducing income inequality in Africa and Pakistan. Does distance higher education also play a role in increasing the income of low-income groups and promoting educational equity? By using quantile regression method, this study measured the returns to distance higher education of different quantiles, to determine which income group received higher returns through distance higher education, and to compare these with face-to-face higher education. This study sought to address gaps in the literature on return to distance higher education.

Research Design and Data

Theoretical Framework

Human capital theory holds that receiving education is an element in the process of human capital accumulation (Gillies, 2017). At the same educational level, different people accumulate the same human capital, so there may be no differences in return between distance and face-to-face education. Similarly, there may also be no significant differences in return to education among distance education learners with the same education but different income levels.

According to screening theory, education plays a signal function. In China, distance education is inferior to face-to-face education in terms of student quality and social reputation(Chen & Wang, 2010), which sends out a negative signal in the labor market. So, the return to distance education may be lower than those to face-to-face education. With expansion in the scale of higher education, no matter what the trends in distance and face-to-face education, according to human capital theory, there may be no significant differences in return to education. But according to screening theory, in China's labor market, the return to distance education may be lower than that of face-to-face education. This study explored changing trends in return to distance higher education and face-to-face higher education. It also compared the return to distance higher education from two key aspects: (a) in different periods under the same degree, and (b) at different income levels.

Method

The Mincer earnings function is the most popular model in economics for analyzing factors that influence income (Heckman et al., 2003). Most studies use the Mincer earnings function to measure the rate of return to education; it places individual incomes, years of education, years of employments, and square of years of employed into a semi-logarithmic equation and estimates the marginal income of education through regression analysis. The Mincer earnings function is as follows:

$$\text{Ln } Y = a + b^*S + c^*EX + d^*EX2 + \varepsilon \qquad (1)$$

Y is individual incomes from labor, Ln Y is the natural logarithm of individual incomes, S represents the education year, X is the worker's years of employment, a is the intercept, and ε is the residual term. The term b is the increased proportion of individual incomes with an increase of one year of education—namely

Mincer rate of return to education. The Mincer rate of return to certain education levels is usually calculated by placing the sample of that education level and the sample of its lower education level into the regression equation.

Distance higher education in China only includes junior college and undergraduate. The regression equation for calculating the return to junior college and undergraduate needs to include the samples of either undergraduate and senior high school, or junior college and senior high school, respectively.

To measure the differences of return to distance higher education for various income groups, this study used the quantile regression method initially proposed by Koenker and Bassett (1978). Compared with ordinary least squares (OLS), quantile regression has two advantages. First, it is widely applied, and it is stable. The conventional regression model explores the influence of explanatory variables on the conditional expectations of dependent variables, which is a kind of mean reversion. The random error of the conventional regression model needs to comply with the basic condition of normal distribution of zero-mean, homoscedasticity, and zero covariance. The explained variables often have extreme values. In the conventional model, influences at the head end and tail end of the explained variables are difficult to measure. Quantile regression considers the influence of different extreme values, so it is more stable in analyzing extreme values and outliers. Second, it can describe the complete picture of the conditional distribution of explained variables. Quantile regression can fit the distribution information of data and make a regression analysis on explained variables based on its conditional quantile. In OLS regression model, the conditional expectation expresses the concentrated trend of the data by fitting the mean value, which cannot reflect the conditions of data at different stages. But quantile regression can describe the effect of explained variables at different stages. Therefore, this study used quantile regression rather than OLS regression. Quantile regression is the regression of whole samples, which reflects the influence of different quantiles of whole samples. It can handle comparative analysis of the data from different quantiles.

The use of quantile regression can more accurately describe the influence of distance higher education on learners' incomes at different income stages. The study took five quantiles of 10%, 25%, 50%, 75%, and 90% to explore the income distribution of distance higher education at different quantiles.

Data

This study used nationally representative data from Chinese Family Panel Studies (CFPS), a comprehensive national bank of social tracking data from a survey conducted by China Social Science Survey Center, Peking University. Most representative national data were not able to distinguish distance education samples from face-to-face samples. CFPS demonstrated diverse distribution in terms of family, geographical, and occupational features, as well as other aspects. CFPS tracks data every two years; this study analyzed data from 2010, 2012, 2014, 2016, and 2018. In mainland China, only undergraduate and junior college degree programs are available via distance higher education, so this study explored learners at these levels, and created samples whose highest degree was high school as a base line. Since the information from CFPS on years of employment was not complete, this study used age – years of education – 6, a metric that is widely used, as a replacement (Romele, 2012; Shen & Zhang, 2015).

Standard Mincer earnings function only controls for an individual's work experience. Graduates' return to education may be affected by other factors. Many studies have added a series of control variables, referred to as extended Mincer function. Based on standard Mincer earnings function, this study added control variables that may affect individual income such as gender, region, parents' education, public or non-public sector, or urban and rural areas (Johnson & Chow, 1997; Shen & Zhang, 2015). This study also compared the regression results between extended Mincer earnings function and standard Mincer earnings function.

To define and assign specific variables, the sample was drawn from the eastern region, so two dummy variables--central and western--were constructed. Dummy variables were also set for (a) geography (urban, 1; rural, 0); (b) sector (public sector, 1; non-public sector, 0); and (c) gender (male, 1; female, 0), respectively.

Table 1

Variables Defined

Variable	Description
Dependent	Logarithm of income
Independent	Years of education
	Years of employment
	Square of years of employment
	Gender (male = 1, female = 0)
	Sector (public = 1, non-public = 0)
	Geography (urban = 1, rural = 0)
	Region (two dummy variables: central region =1, eastern region=0; western region =1, eastern region=0)
	Father's years of education
	Mother's years of education

Calculating return to education for distance undergraduate and distance junior college learners required that the sample use the highest degree of high school as its base line. The samples for this study were determined according to learning level and category: high school, face-to-face junior college, distance junior college, face-to-face undergraduate, and distance undergraduate. Table 2 lists the sample sizes for each year and the distribution of the five sample types.

The income for all samples was positive, and as all were employed, their ages were less than 65 years. There were 3,098 valid samples of distance higher education, including 1,910 distance junior college samples and

1,118 distance undergraduate samples. From 2010 to 2018, the sample sizes for each year are 769, 666, 532, 581, and 550 respectively.

The most important innovation of the study was to use quantile regression to analyze the income of those in distance higher education among different income groups. A second innovation was the use of multi-year tracking samples to conduct the empirical analysis.

Table 2

Sample Sizes, 2010 to 2018

Sample type	2010	2012	2014	2016	2018	Total
High school	2,192	2,095	1,828	2,611	1,979	10,705
Face-to-face junior college	429	595	485	484	451	2,444
Distance junior college	499	416	331	354	310	1,910
Face-to-face undergraduate	384	428	394	449	489	2,144
Distance undergraduate	270	250	201	227	240	1,188
Total	3,774	3,784	3,239	4,125	3,469	18,391

The Results of Empirical Study

Table 3 and Figure 1 show the changes of return to distance higher education and face-to-face higher education obtained from standard Mincer function (without adding control variables) by using OLS and quantile regression. In Table 3, almost all coefficients of quantile regressions are significantly positive, and only one coefficient is not significant. Among all significantly positive coefficients, the vast majority have a significance level of $p < 0.01$. One reason was the quality of the data; it was sufficiently representative and the sample size was large enough. In addition, in all years and across different income groups, whether distance education or face-to-face, the fact of receiving higher education effectively predicted individual income. The following findings can be found from the Table 3 and Figure 1.

Figure 1

Changing Trends of Return to Distance Higher Education (Standard Mincer Earnings Function): 2010 to 2018 Quantiles

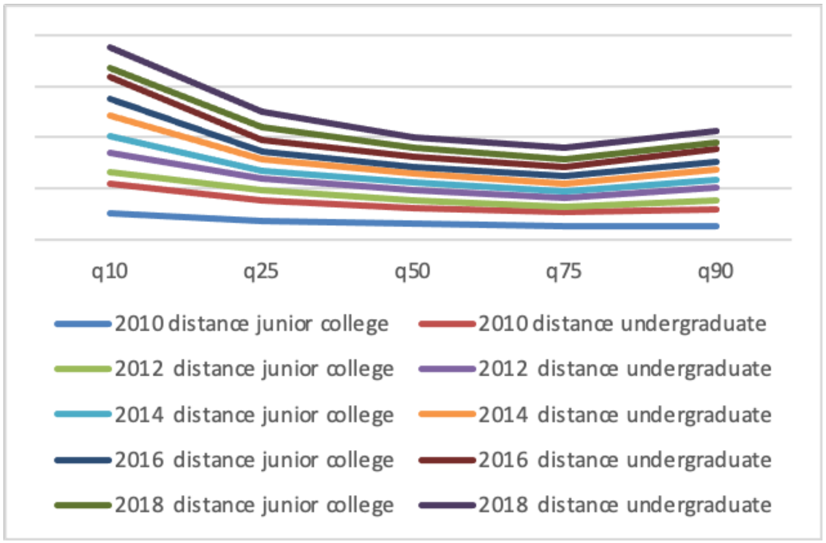

Table 3

Quantile Regression Analysis of Standard Mincer Earnings Function

Year	Sample	OLS	q10	q25	q50	q75	q90
2010	Face-to-face junior college	0.203***	0.252***	0.183***	0.158***	0.150***	0.162***
	Distance junior college	0.192***	0.254***	0.183***	0.156***	0.125***	0.128***
	Face-to-face undergraduate	0.226***	0.263***	0.212***	0.198***	0.204***	0.218***
	Distance undergraduate	0.198***	0.289***	0.195***	0.144***	0.139***	0.161***
2012	Face-to-face junior college	0.109***	0.136***	0.080***	0.080***	0.089***	0.116***
	Distance junior college	0.107***	0.120**	0.104***	0.081***	0.060***	0.091***

	Face-to-face undergraduate	0.145***	0.125***	0.122***	0.129***	0.156***	0.172***
	Distance undergraduate	0.121***	0.185***	0.109***	0.101***	0.086***	0.131***
2014	Face-to-face junior college	0.115***	0.136**	0.124***	0.079***	0.076***	0.113***
	Distance junior college	0.095***	0.165***	0.078**	0.081***	0.063***	0.068***
	Face-to-face undergraduate	0.164***	0.231***	0.151***	0.111***	0.137***	0.171***
	Distance undergraduate	0.111***	0.193***	0.111***	0.081***	0.078***	0.110***
2016	Face-to-face junior college	0.063***	0.051	0.044*	0.064***	0.100***	0.123***
	Distance junior college	0.072***	0.167***	0.081***	0.068***	0.065***	0.070***
	Face-to-face undergraduate	0.111***	0.128***	0.102***	0.098***	0.109***	0.141***
	Distance undergraduate	0.114***	0.213***	0.114***	0.098***	0.095***	0.126***
2018	Face-to-face junior college	0.067***	0.083*	0.101***	0.069***	0.059***	0.072***
	Distance junior college	0.088***	0.098**	0.120***	0.082***	0.079***	0.060***
	Face-to-face undergraduate	0.147***	0.198***	0.162***	0.125***	0.135***	0.156***
	Distance undergraduate	0.124***	0.195***	0.160***	0.101***	0.112***	0.117***

Note. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

First, distance higher education can bring considerable monetary benefits for learners. The return to distance higher education from 2010 to 2018 was considerable. This demonstrated that distance higher education in China, where higher education has shifted from massification to popularization stage (Ministry of Education of the People's Republic of China, 2019), still has considerable investment value for individual learners even though it was once ignored by the public. Considering its large scale, distance higher education has generated positive social effect, a point of pride for distance higher education practitioners.

Second, the low-income group derived notably higher incomes from distance higher education. In 2010, along with the increase of individual incomes within the samples, the return to distance junior college showed a notable decline. This trend indicated that, compared with high-income groups, the low-income groups of distance junior college learners had higher returns to education. For distance undergraduate students, the return to education tended to decline as income increased, but then increased after the 75% quantile. In general, the low-income learners still had the highest return to education. In 2012, 2014, and 2016, with the increase of income, the returns to education of both distance junior college and distance undergraduate students decreased at first and then increased after the 75% quantile. The low-income learners of these three years had the highest return to education, and the pattern was consistent. In 2018 the situation was more complicated. Along with the increase of income, the distance junior college sample showed an increase trend at first and then decreased. The highest point of return to education for distance college was at the 25% quantile level. Distance undergraduate showed a decreasing trend at first and then increased after the quantile of 50%. But the low-income learners still had the highest return to education. In most cases, low-income learners received higher returns from distance higher education. This is the same as the conclusion in many face-to-face education studies (Ginting et al., 2020; Hofmarcher, 2021) that education can effectively reduce poverty. Distance higher education can also reduce the gap between high and low income as well as promote social equality.

Third, in most cases from 2010 to 2018, within the same degree, the returns to distance higher education were lower than to face-to-face higher education. However, in several quantiles, the returns to distance higher education were not lower than to face-to-face higher education. Specifically, in 2010, the return to distance junior college and distance undergraduate at the 10% quantile was higher than to face-to-face junior college and face-to-face undergraduate. At the 25% quantile, the return to distance junior college was equal to face-to-face junior college. In 2012, at the 25% and 50% quantiles, the returns to distance junior college were higher than to face-to-face junior college. At the 10% quantile, the return to distance undergraduate was higher than to face-to-face undergraduate. In 2014, at the 10% and 50% quantiles, the returns to distance junior college were higher than to face-to-face junior college. In 2016, below the 50% quantile, the return to distance higher education was higher than to face-to-face higher education. In 2018, below the 75% quantile, the return to distance junior college was higher than to face-to-face junior college. This indicated that, for low-income learners, the return of investment for distance higher education was higher than for face-to-face higher education. This finding further verified previous research findings that distance higher education notably promoted the incomes of economically disadvantaged groups (Li, Li & Zhang, 2015).

Fourth, regardless the result of quantile regression, the OLS result shows that, from 2010 to 2018, both distance higher education and face-to-face higher education showed a notable decreasing trend. But from 2016 to 2018, compared with face-to-face education, distance junior college and undergraduate showed a dramatic increase. Further analysis is needed to determine whether the increase trend will continue.

Table 4 and Figure 2 illustrate the quantile analysis results of extended Mincer earnings function after adding factors such as gender, region, sector, urban and rural, as well as parents' education levels. Compared to Table 4 and Table 3, although more coefficients became insignificant, most coefficients, by far, were still positive and significant. This means that even after controlling for these factors, distance higher education still effectively predicted learners' income.

From Figure 2, after adding control variables, it is evident that the highest point of return to distance higher education for each year was mainly distributed at the 10% quantile. Compared with face-to-face education, after adding control variables, the returns to face-to-face education were still higher than distance higher education in most quantiles. The returns to distance higher education were higher in few quantiles, mainly concentrated at the 10% and 25% quantiles. Comparing standard Mincer earnings function and extended Mincer earnings function, there was no essential difference between the two, which indicated that the empirical results of this study were firm.

Figure 2

Changing Trends of Return to Distance Higher Education (Extended Mincer Earnings Function): 2010 to 2018 Quantiles

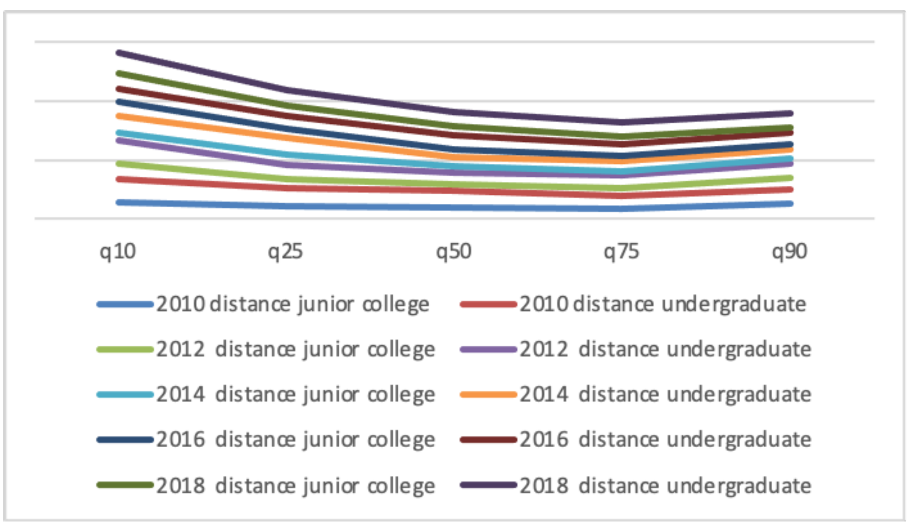

Table 4

Quantile Regression Results of Extended Mincer Earnings Function

Year	Sample	OLS	q10	q25	q50	q75	q90
2010	Face-to-face junior college	0.152***	0.153***	0.100***	0.138***	0.146***	0.125***
	Distance junior college	0.124***	0.140***	0.109***	0.093***	0.088***	0.126***
	Face-to-face undergraduate	0.186***	0.176***	0.155***	0.170***	0.188***	0.190***
	Distance undergraduate	0.150***	0.195***	0.151***	0.145***	0.111***	0.129***
2012	Face-to-face junior college	0.100***	0.149**	0.087***	0.073***	0.092***	0.095***
	Distance junior college	0.089***	0.130**	0.077***	0.055***	0.063***	0.092***
	Face-to-face undergraduate	0.135***	0.144**	0.119***	0.130***	0.151***	0.174***
	Distance undergraduate	0.108***	0.199***	0.124***	0.094***	0.105***	0.120***
2014	Face-to-face junior college	0.099***	0.020	0.098***	0.074***	0.097***	0.097***
	Distance junior college	0.063***	0.069	0.087**	0.056***	0.039**	0.042
	Face-to-face undergraduate	0.138***	0.150***	0.137***	0.108***	0.109***	0.122***
	Distance undergraduate	0.114***	0.143**	0.136***	0.077***	0.084***	0.083***
2016	Face-to-face junior college	0.054**	0.030	0.045	0.077***	0.099***	0.100***

	Distance junior college	0.075***	0.113*	0.081**	0.069***	0.044**	0.042
	Face-to-face undergraduate	0.100***	0.060	0.106***	0.084***	0.110***	0.102***
	Distance undergraduate	0.111***	0.108**	0.104***	0.112***	0.101***	0.091***
2018	Face-to-face junior college	0.068***	0.020	0.080***	0.061***	0.077***	0.083**
	Distance junior college	0.100***	0.132**	0.093***	0.083***	0.063***	0.049
	Face-to-face undergraduate	0.154***	0.212***	0.150***	0.129***	0.147***	0.151***
	Distance undergraduate	0.132***	0.175***	0.127***	0.121***	0.120***	0.120***

Note. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Discussion

The results of both standard and extended Mincer earnings function showed that low-income learners obtained a higher returns to distance higher education, with the highest point of return mainly distributed at the 10% quantile each year. As well, low-income distance higher education learners had higher returns than did face-to-face learners, mainly concentrated at the 10% and 25% quantiles. This indicated that distance higher education had the advantage of increasing returns to education for low-income groups.

This study sought to explain these two findings by considering three factors. First, most distance higher education learners were also employed. Compared with high-income groups of distance and face-to-face learners, the low-income distance higher education learners had less income. With the advantage of combining learning and employment, as well as fewer time and space barriers, the opportunity costs of distance higher education were relatively low. The Mincer earnings function only takes learners' opportunity costs into consideration, so since the low-income distance higher education learners had lower opportunity costs, they received higher returns to education.

Second, the rate of return to education reflects the influence of human capital acquired by individual education on income. Some studies have argued that the quality of distance education is not worse than face-to-face education (Allen & Seaman, 2010; Wang & Wang, 2021). Therefore, distance learners can also obtain human capital as much as those in face-to-face education. Most distance learners have on-the-job experience. Since distance education graduates are more closely related to the labor market and have the advantages of work experience, this helps improve the return to distance higher education.

Third, an employee's degree is usually a key factor for employers as they determine salary. Screening theory holds that education could be used as an indicator of individuals' connate ability (Johnes et al., 2017). Junior college and undergraduate degrees are categorized as higher education. Employees provide employers with obvious signals of personal ability once they have obtained higher education (Spence, 1973), which is conductive to learners' career advancement and increased incomes. Compared to high school education alone, a distance junior college or undergraduate degree may mean promotions and higher salary, and will have great effect on increased incomes.

Regardless which of above is more reasonable, distance education, by eliminating barriers of time and space, has advantages for increasing incomes for low-income learners and promoting social equality.

Implications

This study revealed changing trends in the return to distance education. Compared with face-to-face education, the study found that the return to distance education showed an upward trend in the later years of the sample period and even higher than face-to-face education in some years. The reason may be that the opportunity cost of distance education was lower than that of face-to-face education, highlighting distinct advantages of distance education. At the same time, for low-income people, distance education provided a higher return than for high-income people. The study explained this phenomenon from the perspective of human capital theory and screening theory. With improved quality, distance education can also help learners obtain human capital no less than for face-to-face education. After they acquire higher academic qualifications, low-income groups are able to grow beyond their original educational status and exert a stronger presence in the labor market. This study used human capital theory and screening theory to analyze distance education. The empirical results filled a gap in the existing literature and enriched our understanding of the economics of distance education.

Conclusions and Suggestions

By using China's representative national tracking data, this study used Mincer earnings function and quantile regression method to conduct an empirical analysis of return to distance higher education among different income groups, investigate changing trends, and compare with face-to-face higher education. The paper achieved three findings.

First, distance higher education can bring considerable benefits for learners. With rapidly expanding higher education in China, the scale of distance higher education there is also expanding. However, after controlling for a series of factors, investment in distance higher education can still bring considerable return.

Second, while the return to face-to-face higher education has continued to decline, the return to distance higher education showed an upward trend. From 2010 to 2018, higher education in China showed an important transformation from massification to popularization, along with constant expansion of the scale of postgraduate education (Li & Meng, 2021). Therefore, the decreasing trend of return to education of face-to-face junior college and undergraduate education is understandable. However, from 2016 to 2018, the individual return to education of distance junior college and undergraduate showed a notable increase.

Third, distance higher education has the greatest effect on improving incomes for the low-income group. On the one hand, low-income groups had higher returns on distance higher education than did high-income groups. This study used human capital theory and screening theory to explain this finding—distance learners can obtain human capital as much as can face-to-face learners. After obtaining college and bachelor's degrees, low-income earners move beyond the restrictions of high school qualifications and send a more positive signal to the labor market, thereby getting better jobs and higher salaries. On the other hand, learners can have a higher return from investment in distance higher education than from face-to-face higher education. This is due to the lower opportunity costs for distance learners. This study demonstrated that distance higher education improved the income of vulnerable groups and promoted social equality.

Based on the above findings, this study puts forward the following proposals. First, it is necessary to improve the awareness that distance higher education can lead to increased income for low-income groups. Expanding education will continue to reduce inequality (Coady & Dizioli, 2018). So, it is necessary to increase awareness of the role of distance education in promoting social equity and expand the scale of distance education provisions. Information from this study, if available to potential learners through social media, would attract more low-income learners to invest in distance higher education. As well, education policy makers could use this information to build good policy.

Second, distance higher education should be used as a way to reduce poverty and promote social equality. Existing studies have shown that education can significantly alleviate poverty in underdeveloped regions. (Liu & Li, 2020). Along with comprehensive popularization of network infrastructure and reductions in related costs, it is necessary to continuously provide distance higher education learning resources for low-income groups and the population of underdeveloped areas around the world.

Third, financial support for distance higher education learners should be improved. Some studies have found that tuition fees are a barrier that keep Chinese learners from investing in human capital (Li & Yu, 2022). Currently, there have been few studies and little publicity on financial support to distance higher education students in China. Scholars, policy makers, and publicity departments should draw on the wisdom of the masses to promote financial support to low-income learners distance higher education learners (e.g., tuition remission, student loans). This would address the problem of low-income learners denied distance higher education due to lack of funds for tuition fees.

In conclusion, distance higher education is conducive to promoting social equality. However, the empirical findings of this study were not based on causal inference, which means that the relationships among distance education, and both income and equity, may be more complex. And although distance education can bring considerable benefits, there are also risks. Follow-up research should continuously track return to distance higher education, examine the risk of investment in distance education, and investigate student financial assistance and its effect on distance higher education.

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1 According to the data of National Bureau of Statistics of China (http://data.stats.gov.cn/easyquery.htm?cn=C01), learners in undergraduate and junior colleges of adult education in 2019 numbered 2,131,369, and the total number of adult education and online enrolments was 4,454,497. Adult education and online graduates accounted for 37% of total undergraduate and junior college graduates.