Influence of Fiscal education Expenditure on China's Economic Growth:

New Evidence Using Quantile-on-Quantile Regression Approach

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ABSTRACT
This article applied the novel quantile-on-quantile regression model (QQ) to reconsider the impact of fiscal education expenditure on China's economic growth. It focuses on a sample of 510 consisting of 51 first- and second-tier cities of China from 2010 to 2019. The empirical results are as follows: The estimated results of the fiscal education expenditure (EDU) on China's economic growth (GDP_pc) are fluctuated across quantiles, instead of being depicted as a plane area. A drastically sharp decrease appears in the combination of quantiles of EDU (0.25-0.5) and quantiles of GDP_pc (0.75-0.9), and, surprisingly, an increase shows up in the area of the quantiles-of-EDU range from 0.5 to 0.75, and the quantiles of GDP_pc range from 0.25 to 0.5, as well as in the range from 0.5 to 0.75.

Keywords: *Fiscal education Expenditure, Economic Growth, Quantile-on-Quantile, Quantile regression.*

1. INTRODUCTION

The government expenditure on education is an important material basis for the development of education. Moreover, education is a major element in the quality of the nation and the long-term development of the country. By increasing the government expenditure on education, the state is fundamentally providing a guarantee for providing good education and improving the quality of it. With sufficient funds to upgrade hardware facilities, improve the standard for teachers, update the philosophy of schooling, and align with international education standards, all of these are conducive to the steady improvement of China's educational standards, narrowing the gap between China and developed countries and producing more outstanding talents. The *Highlights of the Ministry of Education's Work in 2022* released by China proposes to implement the strategic position of prioritizing educational development. China insists that the ratio of national fiscal education expenditure to gross domestic product (GDP) should be "no less than 4%". The government ensures the intensity of financial educational expenditure and accelerates the expenditure progress. The Chinese government will ensure that educational expenditures in the general public budget increase year by year and ensure that education expenditures increase according to the number of students in school.

Schultz first proposed in 1961 [1] that education contributes to economic growth and reduces income disparity. Since then, many studies have been conducted to discuss the impact of education on economic growth. However, due to the complicated relationship between the fiscal education expenditure and economic growth, it is hard to quantify the exact effect. Thus, this article introduces a non-linear method, the quantile-on-quantile approach (QQ) proposed by Sim and Zhou[2], to construct estimates of the effect that the quantiles of the fiscal education expenditure has on the quantiles of GDP per capita.

The remaining sections of the study are structured as follows: the second section reviews relevant literature. The description of data applied in the study and the theory of the quantile-on-quantile regression model as well as the construction of specific models are placed in the third section. The fourth section discusses the empirical results, especially the quantile-on-quantile regression (QQ) estimates. The last section proposes a conclusion based on the results.

2. LITERATURE REVIEW

Literature concerning the education expenditure issue is relatively abundant. Especially, the topic discussing the relationship between educational expenditure and economic growth is a lively discussion. Vermeulen (2018)[3] explores the link between the decentralization of educational funding at the local level and inequality in outcomes. Tchamyou et al. (2019)[4] assess the role of ICT in modulating the impact of education and lifelong learning on income inequality and economic growth. Nazukova (2020)[5] discusses practical approaches to financing various levels of education at the expense of public and private funds, where the latter are presented in the context of private funds and state transfers to families with students -- that is public-to-private transfers. Snower et al. (2020)[6] examine how economic fragmentation (widening inequality of skills, income and education) gives rise to social fragmentation (via incompatible social identities), generating political fragmentation (via incompatible economic policies). Pimazzoni (2020)[7] shows the impact of the Mexican educational investment, which is not an expense for the country, and views education as a source of social and economic growth; therefore, it is considered an investment.

Moreover, summarizing the econometric models the aforementioned literature has applied, it seems the application of quantile-on-quantile regression approach (QQ) to this issue is still awaiting someone to fill the gap.

That it is necessary to apply non-linear models to test the relationship between variables has been addressed in much previous research[8]. Classical econometric methods, such as ordinary least squares (OLS) and quantile regressions (QR), cannot solve the complexity and might hide some interesting characteristics of the relationship. Instead, based on the QQ method, on the one hand, researchers do not need to sort different regimes, such as Markov-switching approaches, but can present the nonlinear link in an ad-hoc fashion[9]. Thus, the contribution of this paper is to enrich the previous literature by analyzing the relationship between the fiscal education expenditure and China's economic growth using a comprehensive and novel QQ approach.

3. DATA AND METHODOLOGY

3.1. Data source

The yearly data we applied in this study has been collected from the province and national Bureau of Statistics in China. A total of 510 samples from 51 first- and second-tier cities in China, spanning the period of 2010-2019, was selected for the analysis.

The fiscal education expenditure of each city is identified as the independent variable, while taking the GDP per capita of each city as the dependent variable. In general, fiscal education expenditure includes operating expenses for education, capital construction for education and educational surcharge[10]. The fiscal education expenditure and the GDP per capita have been deflated by the GDP and annual consumer price index of the base year 2010, respectively. Definitions are provided in Table 1.

Table 1. Definition of Variables

Variable	Defination	Unit	Data Source
GDP_pc	GDP per capita of each city and logarithmic	Yuan per person	The province and national Bureau of Statistics in China
EDU	Fiscal education expenditure and logarithmic	Ten thousand yuan	

3.2.Methodology

The conventional quantile regression (QR) can merely capture the influence of X variable on the different quantiles of Y variable ,but is unable to uncover the elaborate features of the impact, accounting for extreme observations, which are ignored by conventional OLS methods [9]. The quantile-on-quantile regression approach (QQ) which is modified on conventional quantile regression [11] is able to capture the dependence between the distributions of Y variable and X variable and uncover two nuanced features in the Y–X relationship [2]. In short, that means the QQ approach can provide a lens for the complicated relationship in the Y–X relationship.

Since the independent variable X in this paper refers to EDU, Y refers to GDP_pc , the QQ model can start by incorporating the following nonparametric quantile regression model:

$$GDP\_pc_t = \beta^{\theta}(EDU_t) + u_t^{\theta} \tag{1}$$

where GDP_pc_t is defined as the logarithmic of GDP per capita at year t, EDU_t represents the logarithmic of fiscal education expenditure at year t, θ is the θ^{th} quantile of the conditional distribution of the EDU_t and u_t^{θ} denotes an error term with a zero θ -quantile. Since there is no prior information about how EDU_t and GDP_pc_t are related, the function $\beta^{\theta}(EDU_t)$ is allowed to be unknown.

Then, to analyse the relation between the θ^{th} quantile of GDP_pc_t and the τ^{th} quantile of EDU_t, denoted by EDU^{τ}, Equation (1) is examined in the neighbourhood of EDU^{τ} employing local linear regression. Because $\beta^{\theta}(EDU_t)$ is unknown, this function can be linearized by a first-order Taylor expansion around a quantile EDU^{τ}, as follows:

$$\beta^{\theta}\left(EDU_t\right) = \beta^{\theta}\left(EDU^{\tau}\right) + \beta^{\theta'}\left(EDU^{\tau}\right)\left(EDU - EDU^{\tau}\right) \quad (2)$$

In Equation (2), where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}\left(EDU_t\right)$ with respect to EDU_t, also called the "marginal effect" or response, is similar in interpretation to the slope coefficient in a linear regression model. A prominent feature of Equation (2) is that the parameters $\beta^{\theta}\left(EDU^{\tau}\right)$ and $\beta^{\theta'}\left(EDU^{\tau}\right)$ are doubly indexed in θ and τ. Given that $\beta^{\theta}\left(EDU^{\tau}\right)$ and $\beta^{\theta'}\left(EDU^{\tau}\right)$ are functions of θ and EDU_t while the EDU_t is a function of τ, that means $\beta^{\theta}\left(EDU^{\tau}\right)$ and $\beta^{\theta'}\left(EDU^{\tau}\right)$ are both functions of θ and τ. Therefore, Equation (2) can be rewritten by redefining $\beta^{\theta}\left(EDU^{\tau}\right)$ and $\beta^{\theta'}\left(EDU^{\tau}\right)$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$:

$$\beta^{\theta}\left(EDU_t\right) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(EDU_t - EDU^{\tau}\right) \quad (3)$$

By substituting Equation (3) in Equation (1), we can obtain the following equation:

$$GDP\_pc_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(EDU_t - EDU^{\tau}\right) + u_t^{\theta} \quad (4)$$

4. EMPIRICAL RESULT

The statistical descriptions of the variables in this paper are shown in Table 2. The numerical value of median and mean of the GDP_pc and EDU are about 10 and 13, respectively. As for the skewness and kurtosis, the former descriptors reflect the asymmetry of the distribution, whereas the latter describes its steepness. The skewness of GDP_pc and EDU are 0.315 and 0.998,respectively.The numerical value of kurtosis is about 4,indicating both of them has a leptokurtic in their distribution .

Table 2. Summary statistics

Descriptor	GDP_pc	EDU
Mean	10.981	13.666
Median	10.961	13.588
Max	12.833	15.608
Min	9.993	12.011
Std. Dev.	0.359	0.645
Skewness	0.315	0.998
Kurtosis	4.080	4.155
Obs	510	510

4.1. Pre-estimation tests

Before undertaking further analyses, it is critical to confirm the relevant features of the series. This study applied the ADF test suggested by Fuller[12] to test the stationary of the variables**;** the outcomes are presented in Table 3**,** and the outcomes unveil that all the series are stationary at level; thus**,** the following statistical analysis will be carried out using the original order data.

Table 3. Unit root test (ADF Test)

Variable	ADF t-Statistic(Level)
GDP_pc	199.347***
EDU	163.603***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2. Quantiles regression approach result

Following most existing studies, this paper uses the 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 95^{th} quantiles as representative to conduct empirical analysis. As the quantile regression(QR) uses several quantile functions to estimate the overall model, we have a lens to look into the influence of the explanatory variables on the explained variables at different quantile points [13]**.** The results of QR and OLS (ordinary least squares) are summarized in Table 4. Except for the Q 0.05 and Q 0.1, the test results of the two models have passed the significance test with a p-value less than 0.01. The estimate indicates that EDU has a positive impact on GDP_pc across the quantiles. By comparing the estimated results of QR, the EDU has its most significant positive impact on GDP_pc at the 75^{th} quantile, past which point, its influence becomes weakened.

Moreover, the results of quantile regression are graphically displayed in figure 1**.** Quantiles regression estimation is in the black line while the 95% confidence interval is denoted by the grey area. The coefficient estimates of variables appear in the vertical axis. The quantile levels are illustrated in the horizontal axis. The OLS estimation is signified by the parallel continuous red line**,** and the 95% confidence interval in the dash red line. Furthermore, the quantile regression (fit) results at different quantile points are depicted in figure 2. The blue continuous line refers to the OLS linear; the dash lines refer to different quantile points from low to high quantiles, respectively.

Table 4. Quantiles regression result

Quantiles levels	EDU
Q0.05	0.088 *
Q0.1	0.083
Q0.25	0.240***
Q0.5	0.211***
Q0.75	0.303***
Q0.9	0.208***
0.95	0.128***
OLS	0.221***

Note: * $p < 0.1$, **$p < 0.05$, *** $p < 0.01$

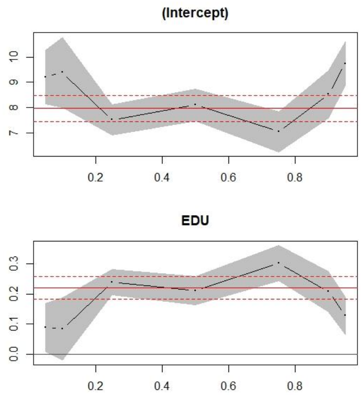

Figure 1 The 95% confidence interval of the quantile regression slope between EDU and GDP per capita.

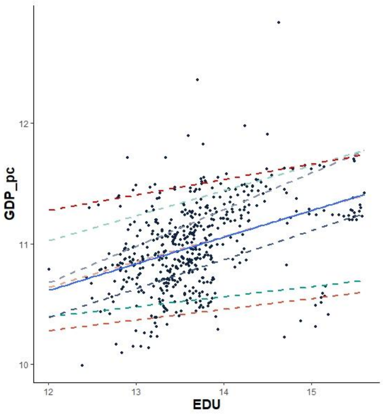

Figure 2 Quantile regression fit results at different quantile points.

4.3. Quantile-on-quantile regression approach result

The quantile-on-quantile regression approach (QQ) outcomes are graphically presented in Figure 3. The figure displays the slope estimates $\hat{\beta}_1(\theta,\tau)$, which catches the influence of τ^{th} the quantile of EDU on the θ^{th} quantile of GDP_pc for a broad range of combinations. The slope coefficients lie on the z-axis, and the quantiles of EDU and GDP_pc are depicted on the x and y-axes, respectively.

The impact of the EDU on the GDP_pc appears weak for most quantile combinations. Interestingly, the estimate results are fluctuated around zero, instead of being depicted as a plane area. However, there is a sharp decrease in the slope estimates between the lower quantiles of EDU (0.25-0.5) and the high quantiles of GDP_pc (0.75-0.9). While the quantiles of EDU range from 0.5 to 0.75 and the quantiles of GDP_pc range from 0.25 to 0.5 as well as range from 0.5 to 0.75, the slope coefficient arises drastically.

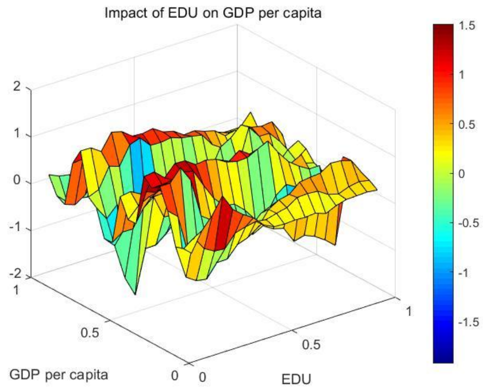

Figure 3 Quantile on Quantile Regression (QQR) estimates.

4.4. Robustness check

In this portion, by comparing the results of quantile-on-quantile regression approach (QQ) estimates with the quantile regression (QR), we can recognize that the findings of QQ estimates are more or less consistent with the findings of QR. The QQ approach regresses the θ^{th} quantile of the EDU on the τ^{th} quantile of GDP_pc; therefore, its parameters can be explained by θ and τ. Because the QR parameters are only explained by θ , the QQ approach can be referred to as the "decomposition" of the QR estimates [2]. Based on this principle, approximate estimates of the QR should be recovered from the QQ estimates. Denoting the slope coefficient of QR as $\gamma_1(\theta)$, the impact of EDU on GDP_pc can be written as follows:

$$\gamma_1(\theta) \equiv \hat{\hat{\beta}}_1(\theta) = \frac{1}{S}\sum \hat{\beta}_1(\theta,\tau) \tag{5}$$

where S = 20 is the number of quantiles θ = [0.05, 0.10, …, 0.95]. The outcome is depicted in figure 4; estimations of parameters for quantile regression are presented by continuous black lines. Dashed red lines present the averaged quantile regression estimations at various quantiles of EDU.

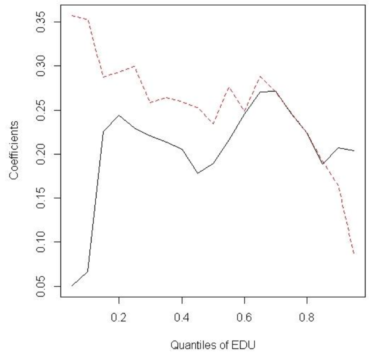

Figure 4 Comparison of QQ and QR.

4. CONCLUSION

Since fiscal education expenditure and economic growth vary across cities of different sizes in China and the provincial government level in China is more of a macro-planning agency, public funding is mainly spent at the municipal government level. Therefore, this paper selects 51 first- and second-tier municipal areas in China as the sample to obtain more reliable and robust empirical results than the previous study by constructing the quantiles-regression model and quantile-on-quantile model. We hope the results can provide more detailed information of the role played by fiscal education expenditure in promoting economic and social development. The array of results from the empirical analysis is outlined as follows:

Based on the quantile regression approach (QR), the estimate shows that EDU has a positive impact on GDP_pc across the quantiles, at 75^{th} quantile where its most significant positive impact on GDP_pc appears, and past that point, its influence becomes weakened. Based on the quantile-on-quantile regression approach (QQ), the estimated results of the EDU on the GDP_pc fluctuate around zero, instead of being depicted as a plane area. Furthermore, a drastically sharp decrease occurs in the combination of quantiles of EDU (0.25-0.5) and quantiles of GDP_pc (0.75-0.9), and surprisingly an increase shows up in the area of the quantiles of EDU range from 0.5 to 0.75, and the quantiles of GDP_pc range from 0.25 to 0.5 as well as range from 0.5 to 0.75.

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