Research Article

Higher Education and Productivity in China

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Abstract

This paper examines the impact of higher education on total factor productivity in China using province-level panel data over the period of 1995-2016. The results show that higher education has a significant U-shaped impact on total factor productivity with a threshold value of 0.323, indicating that higher education development would have a positive impact on total factor productivity after the ratio of college graduates to population exceeds 32.3%. Further analysis reveals that the impact of higher education on total factor productivity is mainly through the Technical Efficiency channel and the Scale Efficiency channel. Moreover, according to the results of the paper, higher education in most provinces of China's is still below the threshold level, suggesting that developing higher education would be an important policy strategy to promote productivity in China.

Keywords

Higher Education • Total Factor Productivity • China

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Higher education plays an important role in both economic and social development, especially for fast-growing developing countries like China. In the twenty-first century, when economic and social development is even more complex, there is an increasing need for more well-educated labour that are best associated with higher education. As a result, the development of higher education and its connections with economic and social development remain to be central issues on the agenda of policymakers. Among these issues, a key issue that is important, but not yet fully resolved, is whether and how higher education may affect productivity thus affect economic growth.

Despite the inadequacy of the literature on a direct examination of the higher education-productivity nexus, a large strand of literature has discussed the role of human capital in economy growth, where education is considered as an important form of human capital. In an early study, Nelson and Phelps (1966) argue that human capital's impact on total factor productivity contributes to economic growth. In the study of Mankiw, Romer, Weil, (1992), the accumulation of human capital has a positive effect on economic growth. As regards the empirical literature, however, the results are somewhat mixed (Barro, 1991; Mankiw et al., 1992; Benhabib and Spiegel, 1994; Nasrul, 1995; Pritchett, 2001). According to Temple (1999) and Rogers (2008), differences in education quality, specific characteristics and market structures across countries may play a role in the uncertain effect of human capital on economic growth. Other explanations include data reasons like misspecification and measurement error and lack of data quality, especially for the transition economies (Benhabib and Spiegel, 1994; Hanushek and Kimko, 2000; Krueger and Lindahl, 2001; Cohen and Soto, 2007; Ahsan and Haque, 2017). In the study of Romer (1990), the level of human capital can explain the economic growth for higher level of human capital enhance productivity, while the improvement of basic knowledge like literacy rate only plays a limited role. Hansen (1999) also confirms that, the positive impact of human capital on growth only occurs when the economy develops into a certain level. Levin (1991) provide possible ways that higher education may have a positive impact on productivity for given resource levels. Benhabib and Spiegel (1994) find that education affects technology improvement and results in changes in economic growth. Kremer, Bick, & Nautz (2013) extends Hansen's model by using dynamic panel data model. In the study of Schündeln and Playforth (2014), social returns to human capital should also be taken into consideration.

To assess the effect of human capital on economic growth, different estimation methods and data sets have been used in the existing literature. In the study of Krueger and Lindahl (2001), initial level of education significantly affects growth in low and middle income countries, but this does not hold in developed countries. Yao and Zhang (2001) use province-level panel data model and find that human capital is positively associated with economic growth. In the study of Ding and Knight (2011), the authors use Generalized Method of Moments (GMM) method to examine the effects of human capital accumulation on economic growth and confirm a positive effect of human capital on economic growth. However, the cross-section regressions in Chen and Fleisher (1996) and the panel estimations in Wei, Liu, Song, & Romilly (2001), Chi (2008) and Li, Lai, Wang, & Zhao (2016) do not find significant impacts of human capital on economic growth. As for the relationship among human capital, productivity and economic growth in China, a direct examination of how higher education may affect total factor productivity seems to be largely absent,

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although there are studies showing that higher education leads to a large gap in regional growth rate (Chen and Fleisher, 1996; Fleisher and Chen, 1997; Demurger, 2001), or that higher educated workers contributes to higher marginal products (Fleisher and Wang, 2004; Fleisher *et al*., 2006), or that higher education contributes to economic growth (Song, 2018; Zhang and Zhuang, 2011).

To sum up, while there is a large body of literature on the relationships between human capital and economic growth or productivity, very few have discussed whether and how higher education may affect productivity, which leaves a major gap in our understanding of the relationships between higher education, productivity and economic growth. Against this background, in this paper we attempt to make a first step in addressing this inadequacy by using province-level panel data from China over the period of 1995-2016. The main contributions of this paper can be summarized as follows.

First, while a large body of literature have discussed the role of education in economic development, very few have directly investigated the relationship between higher education and productivity, especially for developing countries like China. This paper attempts to fill this gap partially by providing empirical evidences on the relationships between higher education and various indicators of productivity using panel data estimation. This helps to establish a direct link between higher education and productivity, which in turn extends our understanding of the role of higher education in economic development.

Second, we find new evidences showing that there exists a U-shaped relationship between higher education and total factor productivity, which is in contrast to the majority of the previous studies which typically assume linear relationships in their analysis. As one can easily see, a U-shaped relationship means that productivity can be improved only after the level of higher education reaches a threshold value, pointing to an even more important role of developing higher education than the traditional linear positive relationship documented in the previous literature.

Third, we show that the U-shaped relationship between higher education and total factor productivity remains quite robust after controlling for a variety of macroeconomic variables such as CPI, real GDP per capita, industry structure, infrastructure, trade openness, real GDP, and government size. Moreover, our main results are also shown to be robust under different estimation methods, which further strengthens the validity of our conclusions.

The rest of the paper is organized as follows. Section 2 describes the data and discusses the methodology. Section 3 presents the empirical findings. Section 4 concludes the paper.

Methodology and Data

Data and variables

To investigate the relationship between higher education and productivity growth, we use data of 30 provinces of China covering the period from 1995 to 2016.

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Our dependent variable is Total Factor Productivity (TFP), which is calculated by Malmquist productivity index (MPI) and consists of four sub-indices: Technical Efficiency (TE), Technical Progress (TP), Pure Technical Efficiency (PTE), Scale Efficiency (SE). MPI measures the productivity changes along with time variations and can be decomposed into changes in efficiency and technology with DEA-like nonparametric approach. The MPI can be expressed in terms of distance function (E) as Equation (1) and Equation (2) using the observations at time t and t+1:

$$MPI_I^t = \frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \tag{1}$$

$$MPI_I^{t+1} = \frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \tag{2}$$

The geometric mean of MPI in Eqs. (1) and (2) leads to the following equation:

$$MPI_I^G = (MPI_I^t MPI_I^{t+1})^{1/2} = \left[\left(\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \right) \cdot \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \right) \right]^{\frac{1}{2}} \tag{3}$$

The input oriented geometric mean of MPI can be decomposed using the concept of input oriented technical progress (TP) and input oriented technical efficiency (TE) as given by Equation (4):

$$MPI_I^G = (TE_I) \cdot (TP_I^G) = \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \right) \cdot \left[\left(\frac{E_I^t(x^t, y^t)}{E_I^{t+1}(x^t, y^t)} \right) \cdot \left(\frac{E_I^t(x^t, y^t)}{E_I^{t+1}(x^{t+1}, y^{t+1})} \right) \right]^{1/2} \tag{4}$$

where the first and second terms in Eq. (4) represent the technical efficiency (TE) and the technical progress (TP), respectively. In addition, by utilizing both CRS and VRS DEA frontiers to estimate the distance functions in Eq. (4), the technical efficiency can be further decomposed into scale efficiency (SE) and pure technical efficiency (PTE) as follows:

$$SE = \left[\frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1}) / E_{crs}^{t+1}(x^{t+1}, y^{t+1})}{E_{vrs}^{t+1}(x^t, y^t) / E_{crs}^{t+1}(x^t, y^t)} \cdot \frac{E_{vrs}^t(x^{t+1}, y^{t+1}) / E_{crs}^t(x^{t+1}, y^{t+1})}{E_{vrs}^t(x^t, y^t) / E_{vrs}^t(x^t, y^t)} \right]^{1/2} \tag{5}$$

$$PTE = \frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1})}{E_{crs}^t(x^t, y^t)} \tag{6}$$

A more detailed explanation of the calculation method of Malmquist productivity index (Caves *et al*., 1982; Fare *et al*., 1994; Jeanneney *et al*., 2006; Han and Shen, 2015).

The key explanatory variable in our study is higher education (EDU) and its quadratic term (EDU2). As is common in the literature, we use college graduates as a share of local population based on the 2010 census to represent the level of higher education development. As shown in Figs. 1 and 2, these has witnessed a significant improvement of higher education development for each province in China over the sample period of 1995-2006, where the average value of higher education development (as measured by the ratio of college graduates to local population) almost tripled in 2016 (Fig. 2) with an average value of 0.244 than that in 1995 (Fig. 1) with an average value of 0.087.

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Figure 1. Higher education development for each province in 1995.

Note. (1) Higher education development is measured by the ratio of college graduates to local population. (2) Tibet and Taiwan are not included in the analysis due to data availability.
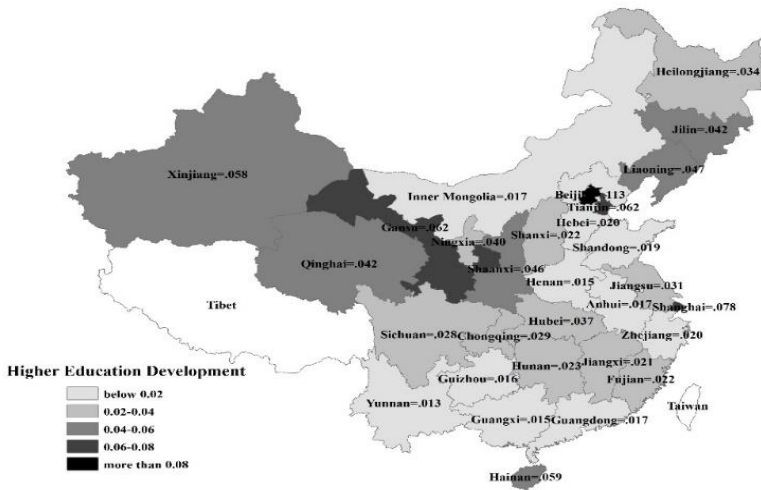

Figure 2. Higher education development for each province in 2016.

Note: (1) Higher education development is measured by the ratio of college graduates to local population. (2) Tibet and Taiwan are not included in the analysis due to data availability.
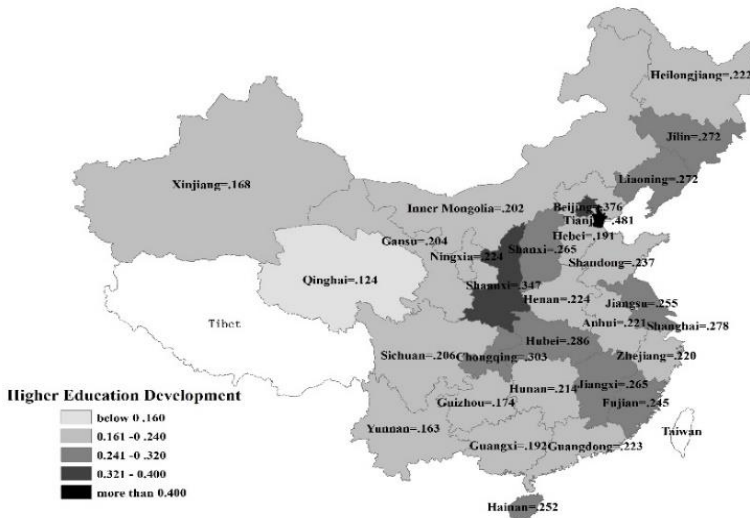
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Finally, to ensure our results are not driven by omitted variables, we also include a variety of control variables that may affect total factor productivity. In particular, the controls that we use include: (1) Inflation, measured by consumer price index (CPI); (2) Economic development, measured by real GDP per capita (RGDPPC); (3) Industry structure (INDUSTRU), measured by the value of secondary and tertiary industries to GDP ratio; (4) Infrastructure development (INFRA), measured by the length of road per 100 squared kilometers (Fleisher *et al*., 2007); (5) Economic size (RGDP), measured by log of regional real GDP; (6) Trade openness (OPEN), measured by the sum of export and import to GDP ratio; (7) Government size (GOVERN), measured by government expenditures as a percentage of GDP. These indicators capture a large variety of potential differences across different provinces in China. All the data of the variables are obtained from National Bureau of Statistics of China. Table 1 reports the summary statistics of the data.

Table 1
Summary Statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
TFP	Total factor productivity	660	0.012	0.089	-0.316	0.538
TE	Technical Efficiency	660	0.997	0.093	0.512	1.904
TP	Technical Progress	660	1.017	0.086	0.449	2.194
PTE	Pure Technical Efficiency	660	0.995	0.078	0.423	1.456
SE	Scale Efficiency	660	1.003	0.064	0.586	1.671
EDU	Higher education	660	0.139	0.092	0.013	0.481
CPI	Consumer price index	660	3.011	4.051	-3.600	21.400
RGDPPC	Real GDP per capita	660	8.133	0.814	6.247	9.877
INDUSTRU	Industry structure	660	0.855	0.079	0.621	0.996
INFRA	Infrastructure development	660	1.145	1.595	0.068	10.271
RGDP	Economic size	660	3.061	0.498	1.662	4.141
OPEN	Trade openness	660	0.304	0.385	0.032	2.043
GOVERN	Government size	660	0.175	0.090	0.049	0.660

Model and estimation methodology

To examine the impact of higher education on total factor productivity, we begin with estimating the following regression model:

$$TFP_{i,t} = \alpha + \beta EDU_{i,t} + \gamma EDU^2_{i,t} + \sum_k \theta_k CONTROLS^k_{i,t} + \varepsilon_{i,t} \qquad (7)$$

where $TFP_{i,t}$ denotes TFP for province i and in year t. $EDU_{i,t}$ is the higher education development indicator as defined earlier. $EDU^2_{i,t}$ is the quadratic term of $EDU_{i,t}$, which is included to capture the potential non-linear effect of higher education on TFP. $CONTROLS^k_{i,t}$ is the vector of control variables as defined before. $\varepsilon_{i,t}$ is the error term.

To estimate the model, both fixed effects (FE) and random effects (RE) estimator are used in the first place. As is standard in the literature, the choice between fixed effects (FE) and random effects (RE) is decided by Hausman test. Further, considering that unobserved province-specific effect is typically present in panel data models, we also use generalized method of moments (GMM) for robustness. As the first-differenced GMM estimator faces the risk of failing to exploit all of the available moment conditions, we use system GMM estimator suggested. The system GMM estimator adds available instrumental variables

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and uses both level and first-differenced regressions in the estimation. Therefore, system GMM is able to control province-specific unobserved heterogeneity. Moreover, system GMM also helps to eliminate the endogeneity of the independent variables and reduce finite sample bias. After including unobserved province-specific effect, Eq. (1) can be rewritten as:

$$TFP_{i,t} = \alpha_0 + \beta EDU_{i,t} + \gamma EDU_{i,t}^2 + \sum_k \theta_k CONTROL_{i,t}^k + \nu_i + \mu_t + \varepsilon_{i,t} \qquad (8)$$

Finally, it should be noted that, to ensure the validity of the instruments in GMM estimation, Arellano and Bond (1991) propose Sargan test with the null hypothesis that there is no correlation between residuals and instruments and second-order serial correlation test (i.e., AR(2) test) with the null hypothesis that there is no second-order serial correlation in the errors. To ensure adequate model specification, both the null hypotheses of the Sargan test and the AR (2) test should not be rejected.

Empirical Results

Table 2
Higher Education and TFP: Baseline Results.

Estimator→	OLS	FE	RE
Variables ↓ →	_TFP_	_TFP_	_TFP_
	(1)	(2)	(3)
EDU	-0.340*	-1.301***	-0.346*
	(0.182)	(0.317)	(0.183)
EDU²	0.691*	2.011***	0.696**
	(0.353)	(0.530)	(0.354)
CPI	0.006**	0.004	0.006**
	(0.003)	(0.003)	(0.003)
RGDPPC	0.057***	0.227***	0.058***
	(0.015)	(0.054)	(0.015)
INDUSTRU	-0.219***	-0.223	-0.217***
	(0.080)	(0.170)	(0.080)
INFRA	0.003	0.003	0.003
	(0.003)	(0.006)	(0.003)
OPEN	0.022*	0.045	0.022*
	(0.012)	(0.029)	(0.012)
RGDP	-0.021	-0.306**	-0.022
	(0.014)	(0.124)	(0.014)
GOVERN	0.062	-0.315**	0.057
	(0.085)	(0.125)	(0.086)
Constant	-0.216**	-0.559**	-0.270**
	(0.097)	(0.271)	(0.118)
F/Wald test	10.80***	10.01***	322.77***
R²	0.31	0.27	0.31
Observations	660	660	660

Note. (1) Standard errors are in parentheses; (2) *, ** and *** denote significant at the level of 10%, 5% and 1%, respectively.

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Regressions results for TFP

Table 2 presents the estimation results for TFP. The first column reports the regression results for Eq. (7) from the pooled OLS estimators. The second and third columns report the results from fixed effects and random effects, respectively. According to results of Hausman test, the null hypothesis is rejected thus the fixed effects results are more precise.

As one can see, the level and quadratic terms of TFP are estimated to be significantly positive and significantly negative, respectively. This indicates a significant U-shaped relationship between higher education and TFP. That is, there exists a threshold value of higher education development, after which the negative impact of higher education on TFP turns positive. According to the results obtained by the FE estimator, which is considered to be more precise as explained earlier, the estimated threshold value of higher education development is 0.323. However, only three provinces (i.e., Beijing, Tianjin and Shaanxi) in our sample exceed the threshold value in 2016 (see Figure 2), suggesting that most provinces of China still need to further develop higher education to improve productivity. As for the control variables, the coefficients on real GDP per capita (*RGDPPC*) are estimated to be significantly positive in pooled OLS and fixed effects regressions, implying fast economic growth contributes to higher productivity. On the contrary, the coefficients on economic size (*RGDP*) and government size (*GOVERN*) are estimated to be significantly negative, implying that an increase in economic and government would lead to lower productivity.

Table 3
Higher education and sub-indicators of TFP.

Panel data estimator→	RE	RE	RE	FE
Variables ↓ →	*TE*	*TP*	*PTE*	*SE*
	(1)	(2)	(3)	(4)
EDU	-0.312	-0.114	0.092	-1.234***
	(0.211)	(0.174)	(0.182)	(0.263)
EDU^2	0.818**	0.007	0.055	1.605***
	(0.408)	(0.330)	(0.354)	(0.440)
CPI	0.008**	-0.001	0.004	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
RGDPPC	0.026	0.029**	0.025*	0.096**
	(0.017)	(0.014)	(0.015)	(0.045)
INDUSTRU	-0.171*	-0.045	-0.151*	-0.275*
	(0.092)	(0.077)	(0.080)	(0.141)
INFRA	-0.004	0.010***	-0.005*	0.004
	(0.003)	(0.003)	(0.003)	(0.005)
OPEN	0.030**	0.009	0.014	0.009
	(0.014)	(0.012)	(0.012)	(0.024)
RGDP	-0.023	0.000	-0.007	-0.085
	(0.016)	(0.014)	(0.014)	(0.103)
GOVERN	0.023	0.021	0.135	-0.349***
	(0.099)	(0.081)	(0.086)	(0.103)
Constant	1.022***	0.732***	0.869***	0.970***
	(0.135)	(0.112)	(0.117)	(0.225)
F/Wald test	151.14***	452.85***	101.07***	4.66***
R^2	0.18	0.41	0.12	0.11
Observations	660	660	660	660

Note. (1) Standard errors are in parentheses; (2) *, ** and *** denote significant at the level of 10%, 5% and 1%, respectively.

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Regressions results for sub-indicators of TFP

The results obtained by using Technical Efficiency (TE), Technical Progress (TP), Pure Technical Efficiency (PTE), Scale Efficiency (SE) as the dependent variables are presented in Table 3.

According to the results of Hausman test, the null hypothesis of the regressions for TE, TP and PTE cannot be rejected, thus the results of random effects are more precise. As for the results for SE, the reverse is true: the results of fixed effects are found to be more precise according to the Hausman test. Note that the estimated coefficients on higher education is statistically significant for TE and SE and insignificant for TP and PTE. This suggest that the impact of higher education on productivity is mainly through the Technical Efficiency channel and the Scale Efficiency channel. In particular, the results in columns 1 and 4 also indicate U-shaped effects of technical efficiency (TE) and scale efficiency (SE) on total factor productivity, for the coefficients of the quadric term of higher education are estimated to be positively significant in the two regressions. For scale efficiency (SE), the result in column 4 suggests that higher education starts to have a positive impact on scale efficiency after the threshold value of 0.384, which is slightly lower than the value estimated for TFP. In contrast, as the level term of higher education in the regression for technical efficiency (TE) is not significant, higher education would have an increasing positive effect on technical efficiency even at very low levels. This indicates that the development of higher education is of crucial importance for enhancing technical efficiency.

Accounting for endogeneity

As discussed in Section 2, to overcome the unobserved heterogeneity and jointly endogenous of the independent variables, we also use system GMM estimator as a robustness test. The results estimated using system GMM for Eq. (8) are presented in Table 4.

From the result in the first column in Table 4, we can see that the level term of higher education is estimated to be significantly negative while the quadric term of higher education is estimated to be significantly positive, indicating that the U-shaped relationship between higher education and TFP still holds under the GMM estimation. Similarly, consistent with the results in Table 3, the impact of higher education on scale efficiency (SE) is significant and U-shaped while that on technical efficiency (TE) is significantly positive at all levels of higher education. Overall, the results in Table 4 suggest that our main results in Sections 3.1-3.2 remain robust after controlling for endogeneity, which further prove the validity of our conclusion.

As for model specification tests, the p-values of the Sargan test and AR(2) test in Table 4 shows that the instruments used are appropriate and there is no evidence of second-order serial correlation in the estimation, suggesting our estimation results are valid.

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Table 4
Higher Education and TFP: System GMM Estimator

Panel data estimator→	System GMM				
Variables ↓ →	*TFP*	*TE*	*TP*	*PTE*	*SE*
	(1)	(2)	(3)	(4)	(5)
EDU	-0.467**	-0.322	-0.096	0.093	-0.457**
	(0.226)	(0.222)	(0.144)	(0.204)	(0.195)
EDU^2	0.898**	0.849**	-0.017	0.052	0.830**
	(0.333)	(0.342)	(0.251)	(0.368)	(0.320)
CPI	0.011***	0.010***	-0.001	0.004*	0.004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
RGDPPC	0.074***	0.028	0.029**	0.027	0.005
	(0.024)	(0.019)	(0.011)	(0.018)	(0.009)
INDUSTRU	-0.315**	-0.199*	-0.044	-0.158*	-0.048
	(0.126)	(0.110)	(0.081)	(0.090)	(0.046)
INFRA	0.002	-0.004	0.010*	-0.005	0.004**
	(0.003)	(0.004)	(0.005)	(0.003)	(0.001)
OPEN	0.023**	0.031***	0.007	0.014*	0.015**
	(0.010)	(0.008)	(0.015)	(0.008)	(0.006)
RGDP	-0.026	-0.020	0.002	-0.007	-0.022
	(0.021)	(0.018)	(0.008)	(0.012)	(0.014)
GOVERN	0.061	0.038	0.030	0.137	-0.158
	(0.140)	(0.126)	(0.109)	(0.109)	(0.102)
Constant	-0.281**	0.911***	0.667***	0.881***	1.018***
	(0.132)	(0.094)	(0.095)	(0.094)	(0.059)
AR(1) test	-3.33	-2.22	-1.79	-2.74	-2.21
(p-value)	0.00	0.03	0.07	0.01	0.03
AR(2) test	1.94	1.11	1.33	0.18	1.56
(p-value)	0.05	0.27	0.19	0.86	0.12
Sargan test	598.77	553.21	532.81	609.68	497.85
(p-value)	0.31	0.57	0.27	0.00	0.43
Observations	660	660	660	660	660

Notes: (1) Standard errors are in parentheses; (2) *, ** and *** indicate that the coefficients are significant at the level of 10%, 5% and 1%, respectively; (3) The p-values of first-order correlation test, second-order serial correlation test and overidentification test are shown in AR(1) test, AR(2) test and Sargan test, respectively.

Conclusion

In this paper, we investigate the effect of higher education on total factor productivity using province-level panel data from China over the period of 1995-2016. The results show that higher education has a significant U-shaped impact on total factor productivity with a threshold value of 0.323, indicating that higher education development would have a positive impact on total factor productivity after the ratio of college graduates to population exceeds 32.3%.

In addition, the results of this paper also reveal that the impact of higher education on total factor productivity is mainly through the Technical Efficiency channel and the Scale Efficiency channel. While the impact of higher education on scale efficiency remains U-shaped with a threshold value of 0.384, its impact on technical efficiency is positive even at very low levels, implying a crucial role of higher education in promoting technical efficiency.

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This paper contributes to the existing literature in three main aspects. First, in contrast to the linear relationship discussed in the traditional literature, we find that there is in fact a nonlinear and U-shaped relationship between education and productivity. Second, we extend the literature by identifying two main channels (i.e., Technical Efficiency channel and Scale Efficiency channel) through which higher education can affect productivity. Third, we find that higher education in most provinces of China's is still below the threshold level, which means that developing higher education would be an important way of promoting productivity in China.

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