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Returns to education in China: a meta-analysis

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ABSTRACT

Within labour economics, returns to education is an area of focused research. Moreover, amongst studies looking at emerging economies, China is the most widely studied economy. While there is a general consensus that returns to education are positive, studies use various datasets and methodologies and consequently present varying estimates of returns to education. We perform a meta-analysis of these estimates of the returns to education in China, addressing issues of heterogeneity in the existing literature and examining whether variations in reported estimates can be explained by study characteristics such as dataset and estimation methods, among others. The meta-regression results show that variations in reported estimates can be accounted for by study characteristics such as data source, estimation method and sample period, among others. The results support the college premium hypothesis and reveal that the returns to education for college graduates are higher than those for other (lower) levels of education.

KEYWORDS
Schooling; earnings; income; China; meta-analysis

JEL CLASSIFICATION
I26; P46; N35

I. Introduction

Education plays an important role in transforming a nation's living standards. Educational outcomes are directly linked to labour market productivity and human capital accumulation, which in turn directly contribute to shaping the future of a nation in the long run. However, owing to the variation in socio-economic conditions, labour market opportunities, economic conditions and the availability of educational infrastructure, returns to education vary significantly between nations and across time periods. This variation is even larger in emerging economies, where resource constraints force governments to prioritise their infrastructure spending. Thus, spending on educational infrastructure has to compete with other necessary infrastructure such as health, transport and social welfare.

In order to fully understand the changing role of education in shaping a nation's future, it is important to measure the returns to an additional year of education. A lot of recent literature has focussed on this fairly broad question. While this is interesting to examine, the biggest challenges come in terms of collecting the data, choosing a methodology and controlling all the other observable and non-observable characteristics that may have a direct or indirect effect on the education–earning relationship. Earlier studies have focussed on a Mincer (1974) type of model specification to estimate the returns to education, using the ordinary least squares (OLS) methodology. Later studies have pointed out that both educational outcomes and earning are affected by the unobserved skills of a person, thereby creating a problem of endogeneity in the education–earnings relationship. These studies suggest the use of instrumental variables (IVs) to correct for this bias, using a Two-Stage Least Squares approach. One of the problems of taking the IV approach is the lack of availability of good instruments in the survey data to correct for endogeneity. Moreover, most of the existing instruments in the literature (such as parental education, spouse education etc.), it can be argued, do not meet the exclusion restrictions required for IVs. Hence, the current literature on returns to education is mixed in terms of methodology.

In this study, we conduct a meta-analysis of studies that examine returns to education in the Chinese context. There are several reasons for focussing on China in particular. First, returns to

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education depend on a number of factors that differ widely from one nation to another. These include economic conditions, cultural attitude towards education, religious practices and government policy towards provision of educational infrastructure. Therefore, it makes sense to conduct a meta-analysis of studies focussing on one nation only. Second, there has been a lot of recent focus on the emerging Chinese economy and the new economic opportunities available to its citizens. This raises an obvious interest in exploring the role of education in facilitating China's transition. Third, it is important to understand the sources of variations (such as datasets, methodology, time period of study etc.) in the returns to education that are reported in existing studies and to have a unified understanding of the role played by education in the Chinese context.

To the best of our knowledge, except for Fleisher, Sabirianova, and Wang (2005b) and Liu and Zhang (2013), no other studies have conducted a meta-analysis of returns to education in China. While this study uses a superset of the studies used in Fleisher, Sabirianova, and Wang (2005b) and Liu and Zhang (2013), the results of the present study is not a duplication of the findings presented by both studies. Fleisher, Sabirianova, and Wang (2005b) compare the growth rate in returns to education in Central and Eastern Europe, China and Russia. In the process, they collect estimates of returns to education in China as well. Liu and Zhang (2013), on the other hand, perform an empirical synthesis for the estimates of returns on education in China only, and this study is thus similar to our own.

We find a number of limitations with these studies and address them in this current study. First, Fleisher, Sabirianova, and Wang (2005b) do not systematically account for heterogeneity in the existing literature. The evidence base on the returns to education in China is quite large and thus is accompanied by significant heterogeneity, which leads to the report of different estimates. We seek to address these issues of heterogeneity towards a statistically verifiable estimate on the returns to education in China. Addressing heterogeneity is also a significant step which makes it possible to accurately compare estimates from different studies. This is important given that the various studies that examine returns to education in China draw on evidence from various datasets and estimation methods. To address the heterogeneity, we adopt multivariate meta-regression models which allow for the inclusion of moderating variables that represent different study characteristics, or to put it differently, that capture heterogeneity.

Second, neither study controls for publication selection bias. Publication selection bias occurs when editors, reviewers and researchers are predisposed to selecting studies with specific results (e.g. statistically significant findings congruent with the prediction of the theory). In the presence of publication selection bias, policy implementation is impeded, and this has been considered a threat to empirical economics, as a literature with a large and significant effect could actually be fraught with bias and be misleading (Stanley 2008). We conduct formal tests to verify whether publication selection bias exists, and we estimate the average returns to education in China after taking account of this bias. Thus, we adopt the precision effect test (PET) and the funnel asymmetry test (FAT) to fill this gap by providing evidence on the 'genuine' effect of education on income in China beyond publication selection bias.

Lastly, since Fleisher, Sabirianova, and Wang (2005b), there has been a significant increase in the literature examining returns to education in China, most of which have been conducted with newer datasets. Given recent trends which suggest that returns to education in China increase over time, it is worthwhile to adopt appropriate and comprehensive techniques to examine the existing empirical literature on this phenomenon. Our empirical approach is therefore based on recent developments in meta-analysis tools (discussed in Section 4) which have not been used in either Fleisher, Sabirianova, and Wang (2005b) or Liu and Zhang (2013).

The rest of this article is organised as follows: Section 2 presents a brief overview of the literature on returns to education in China. Section 3 describes the dataset, and Section 4 describes the meta-analysis tools and methods. Section 5 presents results from the meta-analysis, and Section 6 presents a summary and concluding remarks.

II. Brief overview of the literature

Since Mincer's (1974) seminal work, the study of returns to education has become an important part of economics literature. The focus on Chinese data came about in the 1990s, however. Based on Mincerian models, several studies have provided evidence which suggests that returns to education in China have increased in the last two decades and are now approaching the average returns observed for major market economies (Li 2003; Li and Luo 2004; Zhang et al. 2005; Fleisher et al. 2011). Overall, some major trends have emerged in the literature on returns to education in China.

To begin with, returns to education in China have increased over time, although some evidence suggests otherwise. Studies documenting increasing returns over time often attribute this to China's economic transformation. For instance, data from the 1980s usually point to a low rate of returns to education, with an average of 2.0–4.5% in most studies. Using data from 1986, Byron and Manaloto (1990) show that the rate of return for an additional year of schooling is 3.7%. Meng and Kidd (1997) also found lower returns of 2.5% and 2.7% for 1981 and 1987 data, respectively. Other studies (Maurer-Fazio 1999; Liu 1998; Knight and Song 1991, 1995; Gustafsson and Li 2000) use 1980s data either from the Chinese Household Income Project (CHIP) or from the Urban Household Income Surveys and provide evidence of low returns to education. When Gustafsson and Li (2000) compare results from a 1988 sample with those from a 1995 sample, they report higher returns in 1995. Similarly, Knight and Song (2003) find that the returns to college education rose from 15.1% in 1988 to 40.1% in 1995. Thus, data from the 1980s report lower returns relative to 1990s data, and studies with recent data (from 2000) have shown that there is indeed a rise in returns to education in China (Heckman and Li 2004; Li 2003; Li, Liu, and Zhang 2012; Zhang et al. 2005; Mishra and Smyth 2013). In contrast, some studies use recent datasets (from 2000) and report low returns to education. For instance, Zeng (2004) used 2000 data from Chengdu and reported a returns to education rate of 1%. Similarly, using CHIP 2002 data, Magnani and Zhu (2012) report OLS estimates of the returns to schooling to be 4.2% and 4.1% for females and males, respectively. This is inconsistent with trends which suggest that the returns to education in China increase over time. As such, it is worthwhile to examine returns to education in China over time in the context of a meta-analysis.

Second is the emergence of studies that compare returns to education for females and males (Zhang et al. 2005; Chen and Ju 2003; Li and Ding 2003; Maurer-Fazio 1999; Chen and Hamori 2009; Magnani and Zhu 2012; Ren and Miller 2012a). These studies usually report higher returns to education for females than for males. Exceptions are Chen and Hamori (2009) and Ren and Miller (2012a), who report slightly higher returns for males based on a recent samples from the Chinese Health and Nutrition Survey (CHNS).

Third, recent studies have compared the returns to various levels of education. These studies mostly report higher returns to college education. For instance, Gustafsson and Li (2000) report relatively higher returns to 4-year college education than to upper-middle-school education. Similarly, Chen and Hamori (2009) and Zhang and Zou (2001) also report that returns to college education is higher than those to other levels of education, and these estimates are even higher when adjusted for endogeneity in education. Overall, this strand of literature suggests that returns to education increase with higher levels of education. Furthermore, some studies report a positive correlation between college premium and quality of college (Zhong 2011). Further distinctions are also made in terms of age group and experience. For instance, Liu (1998) suggests that older workers or more experienced workers have lower returns to education than younger workers do.

Further, a number of studies examine returns to education in the context of migration, while a few others compare returns to education in rural and urban China. While most studies examining the returns to education in China use data covering only urban areas, the few studies that do use rural data and/or that compare returns in rural with those in urban areas generally present mixed results (Johnson and Chow 1997; De Brauw and Rozelle 2008; Ren and Miller 2012b; Zhang et al. 2008; Zhao 2007).

Furthermore, various distinctions can be made about the labour force in China. For instance, China has experienced a dramatic surge in the level of rural-urban migration (Messinis 2013), and evidence suggests that the average level of education for migrant workers is lower than that of their urban co-workers but significantly higher than that of the rural labour force (Messinis 2013). The returns to education for migrant workers in China have been examined by several studies, and the consensus is that there are modest returns to schooling, which have improved over time as the Chinese economy has gradually shifted towards a market economy (Li and Zhang 1998; Tao Yang 2004; Zhang and Zou 2007).

Lastly, arguments concerning endogeneity have led to the use of different estimation methodologies, particularly the IV technique, in determining returns to education in China. Following the Mincerian model, several studies have used the OLS methodology to examine the returns to education in China. However, it has often been argued that there are issues concerning the endogenous bias of education (Heckman and Li 2004; Li and Luo 2004; Fleisher et al. 2005a; Arabsheibani and Lau 1999). As such, in examining the returns to education in China, some studies have used IV techniques to address the problem of endogeneity of education (Heckman and Li 2004; Li and Luo 2004; Fleisher et al. 2005a; Chen and Hamori 2009; Messinis 2013; Mishra and Smyth 2013). Commonly used instruments for education include parental education, spouse's education, number of siblings and parental income, among others, and, in most cases, the IV estimates turn out to be higher than estimates obtained from the conventional OLS approach of the Mincer model.

III. Data

The data used in this study are empirical results extracted from existing studies that examine the relationship between education and income in China. Our review of the returns to education literature draws on guidelines proposed by the meta-analysis of economics research-network, which reflect transparency and best practices in meta-analyses (Stanley et al. 2013). We adopt a three-stage search strategy in identifying relevant and reliable empirical literature for our review. The first step is to identify relevant electronic databases to search and also relevant keywords related to education and income. The second is to conduct the electronic database search, after which the results are uploaded into a reference manager for screening. The last stage involves a manual search process of relevant websites.

Overall, we searched seven electronic databases, including the ProQuest database, which in itself includes 32 databases. We searched for journals, working papers and reports, using 10 keywords related to the returns to education literature in China.[1] After removing duplicates, 84 studies were identified to be reviewed for inclusion or exclusion in our study. The study screening process took place in two stages. In the first stage of screening, we reviewed the titles and abstracts of studies. At this point, we examined whether the study focused on China and whether or not the independent variable was education. This title and abstract screening led to the selection of 84 studies for the second stage, which is the critical evaluation or full-text screening stage. Here, we acquired the full text of all 84 studies and examined studies based on their relevance to our research question. We also conducted a manual search by examining the bibliography of relevant studies on the topic to ensure we did not miss out on any studies worth including in our meta-analysis. In the end, we found 59 empirical studies that reported on returns to education in China to be relevant for inclusion in our study.

Given that our objective is to focus on the effects of education on income, we excluded studies that examined the relationship between education and firm productivity in China. Thus, the studies included in our meta-analysis rely on estimating one form or the other of the following Mincer (1974) equation:

$$y_i = \alpha + \beta_1 \mathrm{Edu_i} + \beta_2 \mathrm{Exp_i} + \beta_3 \mathrm{Exp}_i^2 + \beta_4\ X_i + \epsilon_i$$

such that $\mathrm{Edu_i}$ is the years of education or the dummies for education levels, $\mathrm{Exp_i}$ is the

[1]The last search protocol was executed in January 2015.

experience and Exp_i^2 is the squared-experience and X_i is the vector of all the other controls that affect an individual's earnings y_i. Here, β_1 is the key coefficient in understanding the returns to schooling.

We extracted all effect estimates/coefficients as well as other relevant statistics reported in the included studies. Possible alternatives to this would be to extract the average or median for each study or perhaps a single estimate chosen on the basis of sample size or statistical significance. However, these alternatives have some well-documented flaws. First, this selection criterion would be subjective and would therefore be likely to bias our results. Second, using such alternatives would prevent the use of all available information. Lastly, such alternatives are likely to reduce the possibility of replication and comparability of the findings in different meta-analysis (De Dominicis, Florax, and Groot 2008; Stanley 2008; Stanley, Jarrell, and Doucouliagos 2009).

IV. Meta-analysis tools and methods

We adopt five main meta-analysis tools in reviewing the literature on returns to education in China. First, to ensure comparability across studies, we calculate partial correlation coefficients (PCCs), which measure the relationship between education and income while holding other explanatory variables constant. PCCs allow comparability across studies, as they are independent of the metrics used in measuring both the independent and dependent variables (Ugur 2013). A plausible alternative would be elasticities, which are also comparable across studies. However, the information needed to calculate elasticities are not provided by primary studies. As a result, PCCs are used extensively in meta-analysis (e.g. Doucouliagos and Ulubasoglu 2008; Doucouliagos and Stanley 2009; Doucouliagos and Laroche 2009; Hawkes and Ugur 2012; Ugur 2013).

Second, we calculate fixed effect estimates (FEEs) of the PCCs to provide a descriptive summary of the empirical evidence reported by each primary study. Third, we calculate random effect estimates (REEs) for studies pooled together based on the measure of education used. Some studies use years of schooling as the measure of education, while others use dummies for educational level. Thus, we cluster evidence presented in each category and present REEs as an overall descriptive summary of evidence for each category. Fourth, we conduct PETs and FATs. The PETs/FATs make it possible to determine the 'genuine' effect of education on income beyond publication bias. Lastly, we conduct random effect meta-regressions analysis (MRA), which allows us to control for and determine the effects of various moderating variables.

Empirical models

We use the following equations (1) and (2), to calculate PCCs (r_i) and standard errors (se_{ri}), respectively, for each effect-size estimate.

$$r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{1}$$

and

$$se_{ri} = \sqrt{\frac{(1 - r_i^2)}{df_i}} \tag{2}$$

Where t_i and df_i are the t-statistics and degrees of freedom associated with the coefficients or effect-size estimates reported in the primary studies; se_{ri}, is the variance associated with sampling error, and the squared inverse is used as weight to calculate the FEE weighted mean for each study.

Given that the effect-sizes reported by the primary studies are derived from the same population and have a common mean, FEEs are efficient in providing suggestive evidence presented by each primary study (Stanley, Jarrell, and Doucouliagos 2009). We calculate the FEEs' weighted means based on the approach adopted by Stanley and Doucouliagos (2007), Stanley (2008), De Dominicis, Florax, and Groot (2008) and Ugur (2013), among others. They report that the FEEs can be calculated using Equation (3).

$$\bar{X}_{\text{FEE}} = \frac{\sum r_i(1/\text{se}_{ri}^2)}{\sum 1/\text{se}_{ri}^2} \tag{3}$$

Where $\bar{X}_{\text{FEE}}$ is the FEE weighted mean, and all other variables remain as they are above. FEE weighted means distribute weights such that less precise estimates are assigned lower weights and vice-versa. This accounts for within-study variations. However, given that primary studies may be affected by within-study dependence and/or may be subject to publication selection bias, they are only taken as a descriptive summary of the evidence base and not as measures of genuine effect (De Dominicis, Florax, and Groot 2008; Ugur 2013).

We also cluster estimates based on the measure of education used in the primary studies and calculate REE weighted means for each category. Given that each cluster would include estimates from various studies, we require two different error variances in our calculations. The first is se_{ri}^2 as used in Equation (3), and the second is the variance of distribution (σ^2) of the estimates reported in a given cluster. Thus, Equation (4) is used to calculate the REE weighted means.

$$\bar{X}_{\mathrm{REE}} = \frac{\sum r_i(1/\mathrm{se}_{ri}^2 + \sigma^2)}{\sum 1/\mathrm{se}_{ri}^2 + \sigma^2} \tag{4}$$

Where $\bar{X}_{\mathrm{REE}}$ and σ^2 are the REE weighted mean and the variance of PCCs in a given cluster, respectively. REE weighted means assume both within and between-study independence and thus distribute normally around the population mean, subject to any disturbances which arise due to between-study variations (σ^2) and within-study variations (se_{ri}^2). Thus, in the presence of heterogeneity, the REEs are efficient given that they account for both within and between-study heterogeneity (Stanley, Jarrell, and Doucouliagos 2009; Hawkes and Ugur 2012).

However, FEE and REE weighted means do not deal with publication selection bias. To determine if there are issues concerning publication bias and to deal with them, we conduct PETs/FATs and also precision effect estimates with standard error (PEESE). PETs involve the estimation of a weighted least square bivariate model and have been widely used in the meta-analysis literature (e.g. Dalhuisen et al. 2003; Abreu, De Groot, and Florax 2005; Stanley and Doucouliagos 2007; Efendic, Pugh, and Adnett 2011; Ugur 2013). Stanley (2008) shows that Equation (5) can be used to test for publication selection bias (i.e. the FAT) and also for genuine effect beyond bias (i.e. the PET).

$$t_i = \alpha_0 + \beta_0\left(\frac{1}{\mathrm{se_{ri}}}\right) + \varepsilon_i \tag{5}$$

Here, all variables remain as explained above, and t_i is the t-statistic extracted from the primary studies. $1/\mathrm{se_{ri}}$ is the precision, and its coefficient is the measure of genuine effect. The PET and FAT analysis involves testing for $\beta_0 = 0$ and $\alpha_0 = 0$, respectively. The FAT has been identified to have a low probability of rejecting the null hypothesis thus increasing the probability of committing a type II error. However, when selection bias is controlled, Equation (5) still has the advantage of testing for genuine effect (Ugur 2013). Further, Doucouliagos and Stanley (2009) suggest that there is evidence of substantial and severe publication selection bias if $|\alpha_0| \geq 1$ and $|\alpha_0| \geq 2$, respectively.

In addition, Stanley and Doucouliagos (2007) indicate that there is a nonlinear relationship between reported estimates and their standard errors if results from PETs suggest the existence of genuine effect. In such cases, they propose the PEESE analysis to obtain a corrected estimate for β_0. The PEESE model is derived from Equation (6).

$$r_i = \beta_0 + \alpha_0\left(\mathrm{se}_{ri}^2\right) + u_i \tag{6}$$

We divide through Equation (6) by $\mathrm{se_{ri}}$ to obtain Equation (7) in order to address heteroscedasticity concerns.

$$t_i = \beta_0\left(\frac{1}{\mathrm{se_{ri}}}\right) + \alpha_0(\mathrm{se_{ri}}) + v_i \tag{7}$$

We estimate Equation (5) to determine genuine effect beyond bias, and where there is evidence of bias, we estimate Equation (7) with a suppressed constant term.

The PET/FAT and PEESE analysis allows for the determination of genuine effect beyond bias. However, these methods assume that the moderating variables related to each study or that capture study characteristics are equal to their sample means and independent of the standard errors (Doucouliagos and Ulubasoglu 2008; Ugur 2013). Thus, the PET/FAT and PEESE analysis do not include moderating variables. We therefore conduct a multivariate MRA to determine the extent to which moderating variables account for variations in the reported estimates. The MRA also allows us to determine if the association between education and income in China are robust to the inclusion of moderating variables. Stanley and Jarell (1989) propose that Equation (8) can be used to model heterogeneity, and this has been adopted for use by various studies, including Stanley (2008), Doucouliagos and Ulubasoglu (2008), Efendic, Pugh, and Adnett (2011) and Ugur (2013).

$$t_i = \alpha_0 + \beta_0\left(\frac{1}{\mathrm{se_{ri}}}\right) + \sum \beta_k\left(\frac{Z_{ki}}{\mathrm{se_{ri}}}\right) + \in_i \quad (8)$$

Here, Z_{ki} is a vector of binary variables that capture study characteristics and account for variations in primary studies. As before, $1/se_{ri}$ is the precision, and ϵ_i is the disturbance term associated with sampling error.

However, given that primary studies often provide several estimates, the independence among reported estimates can be questioned (De Dominicis, Florax, and Groot 2008). Thus, we account for this multi-level structure and its implied dependence by estimating the following equation:

$$t_{ji} = \alpha_0 + \beta_0\left(\frac{1}{\mathrm{Se_{jri}}}\right) + \sum \beta_k\left(\frac{Z_{ki}}{\mathrm{se_{jri}}}\right) + \in_j + u_{ji} \quad (9)$$

Where, t_{ji} is the ith test statistic from the jth study, and k is the number of regressors or moderator variables. ϵ_j is the study-specific error term. Both error terms ϵ_j and u_{ji} are normally distributed around the PCCs' mean values such that $\epsilon_i \tilde{N}\left(0, \mathrm{se}_{ri}^2\right)$, where se_{ri}^2 is the square of the standard errors associated with each of the derived PCCs, and $u_i \tilde{N}(0, \tau^2)$, where τ^2 is the estimated between-study variance.

To adequately deal with issues of data dependence, we estimate both PET-FAT-PEESE and MRA using the hierarchical linear model (HLM) estimation technique (Goldstein 1995). Due to the multiple estimates reported by primary studies, our data is characterized by an inherent hierarchical structure as several observations are clustered within one study. Thus, in this case, the estimation of our MRA and PET/FAT with OLS may be erroneous and prone to various criticisms. This is particularly the case because the assumption of independent distribution among estimates reported by primary studies may be flawed. The HLM has therefore been employed to deal with the issue of data dependence, as it is often used in meta-analysis to deal with such issues (De Dominicis, Florax, and Groot 2008; Bateman and Jones 2003; Alptekin and Levine, 2012). Furthermore, the likelihood ratio test which compares linear regression to HLM supports the preferences of HLM considering our dataset.

V. Results and discussions

Fixed effect weighted means (overview of evidence base)

(Table 1a and b) present fixed effect weighted means of the PCCs for each primary study that reports years of schooling and educational level, respectively, as measures of education. As shown in (Table 1a), 48 primary studies with a total of 527 estimates use years of schooling as the measure of education. The results indicate that of these 48 primary studies, only 8 studies (16.67% of the total number of studies) with 39 estimates (7.40% of total estimates) present statistically insignificant weighted means.

All statistically significant weighted means are positive. Hence, based on the PCCs calculated for each primary study that uses years of schooling as a measure of education, we conclude that, as expected, the returns to education in China are positive. The net fixed effect weighted average for all 48 studies is also found to be positive, with a magnitude of 0.1807.

From (Table 1b), we note that 26 primary studies with 452 estimates report on the association between various education levels and income. We find that six studies (23.07% of the total number of primary studies) with 35 estimates (7.74%) have statistically insignificant means. We also find that all studies in this category have positive weighted means. This suggests that, based on the PCCs calculated for studies in this category, the returns to education in China are positive as well, with a net fixed effect weighted average of 0.0547.

Overall, without addressing heterogeneity (various dimensions/differences of the research field) or any potential issues concerning selection bias, the existing

Table 1A. Years of schooling and income (overview of evidence base per study – simple and fixed effect weighted means).

Paper	No. of Estimates	Simple Mean	Weighted Mean (FE)	Significance	Confidence Interval
Bishop and Chiou (2004)	2	0.1559	0.1688	No	(−0.4979, 0.8355)
Brauw and Rozelle (2008)	13	0.0007	0.0003	Yes	(0.0001, 0.0006)
Byron and Manloto (1990)	5	0.0007	0.0007	No	(−0.0009, 0.0023)
Chen and Hamori (2009)	8	0.2958	0.3058	Yes	(0.2502, 0.3614)
Cheng and Feng (2011)	9	0.0700	0.0664	Yes	(0.0240, 0.1088)
Fan (2009)	1	0.1506	0.1506		
Fang et al (2012)	20	0.0692	0.0682	Yes	(0.0414, 0.0949)
Fu and Ren (2010)	2	0.1236	0.1236	No	(−0.1827, 0.4300)
Giles et al (2008)	4	0.3541	0.3544	Yes	(0.3205, 0.3883)
Hannum et al (2013)	16	0.0283	0.0333	No	(−0.0078, 0.0743)
Ho et al (2002)	14	0.1748	0.1699	Yes	(0.1401, 0.1997)
Huang et al (2002)	12	0.4757	0.5292	Yes	(0.4034, 0.6549)
Johnson and Chow (1997)	8	0.1711	0.1836	Yes	(0.1270, 0.2402)
Kang and Peng (2012)	56	0.1284	0.0977	Yes	(0.0840, 0.1113)
Kim (2010)	5	0.2397	0.2418	Yes	(0.1511, 0.3324)
Li (2003)	4	0.1572	0.1555	Yes	(0.1348, 0.1763)
Li and Luo (2004)	9	0.1728	0.1798	Yes	(0.1360, 0.2236)
Li et al (2005)	4	0.1518	0.1543	Yes	(0.0826, 0.2260)
Li, Liu, and Zhang (2012)	16	0.1722	0.2039	Yes	(0.1245, 0.2834)
Liu (1998)	10	0.1760	0.1790	Yes	(0.1554, 0.2025)
Luo (2008)	8	0.1218	0.1221	Yes	(0.0900, 0.1542)
Maurer-Fazio (1999)	4	0.2325	0.2354	Yes	(0.1930, 0.2778)
Meng (1995)	6	0.0844	0.0765	No	(−0.0232, 0.1762)
Mishra and Smyth (2013)	26	0.3025	0.3071	Yes	(0.2872, 0.3270)
Ning (2010)	8	0.2989	0.3135	Yes	(0.2355, 0.3915)
Qian and Smyth (2008)	5	0.2921	0.2878	Yes	(0.2197, 0.3559)
Qin et al (2013)	1	0.0170	0.0170		
Qiu and Hudson (2010)	16	0.1001	0.0737	Yes	(0.0397, 0.1077)
Ren and Miller (2012a)	4	0.2111	0.1971	Yes	(0.0940, 0.3003)
Ren and Miller (2012b)	18	0.2296	0.2182	Yes	(0.1602, 0.2762)
Wang (2013)	28	0.1543	0.1549	Yes	(0.1170, 0.1929)
Wu and Xie (2003)	11	0.0890	0.0990	Yes	(0.0210, 0.1769)
Xiu and Gunderson (2013)	20	0.1496	0.1539	Yes	(0.0949, 0.2129)
Zhang et al (2002)	1	−0.0132	−0.0132		
Zhang et al. (2005)	14	0.3451	0.6293	Yes	(0.4289, 0.8298)
Zhang et al (2007)	8	0.2674	0.2966	Yes	(0.1714, 0.4218)
Zhang et al. (2008)	3	0.1348	0.1354	No	(−0.0103, 0.2811)
Zhao (2007)	12	0.1260	0.1331	Yes	(0.0931, 0.1730)
Zhao and Qu (2013)	4	0.0925	0.0956	Yes	(0.0342, 0.1570)
Zhong (2011)	7	0.2667	0.2714	Yes	(0.1846, 0.3582)
Zhu (2011)	36	0.2652	0.2611	Yes	(0.2350, 0.2872)
Yang (2005)	6	0.2220	0.2260	Yes	(0.1982, 0.2537)
Jamison and Van Der Gaag (1987)	2	0.2633	0.2690	No	(−0.1724, 0.7104)
Gregory and Meng and Kidd (1997)	3	0.0371	0.0371	No	(−0.0539, 0.1281)
Sakellariou and Fang (2014)	22	0.1362	0.1380	Yes	(0.1188, 0.1572)
Gao and Smyth (2015)	18	0.2721	0.2802	Yes	(0.2449, 0.3155)
Hu, Guo, and Wang (2014)	6	0.1426	0.1431	Yes	(0.0991, 0.1872)
Mishra and Smyth (2014)	12	0.2943	0.2959	Yes	(0.2622, 0.3296)
Total	527	0.1824	0.1807		

literature on returns to education in China suggests that, whether years of education or dummies for education level is used as a measure for education, the returns to education are positive.

Random effect weighted means

(Table 2) presents random effect weighted means based on four categories formed by the measure of education used. As discussed earlier, REEs assume both between-study and within-study independence and accordingly account for disturbances that may arise due to variations in primary studies.

First, all studies that report estimates with years of schooling as the education measure are pooled together in one cluster. Similarly, we pool together studies that use education level as the measure of education. In addition, we also split studies that report estimates for education level into two categories: college education and above, and other education levels. This segregation allows us to examine if the returns on education are generally higher for individuals with higher levels of education. From (Table 2), the results indicate that an additional year of schooling is associated with an 18.31% increase in income. Similarly, an average of a 9.98% increase in

Table 1B. Educational level and income (overview of evidence base per study – simple and fixed effect weighted means).

Paper	No. of Estimates	Simple Mean	Weighted Mean (FE)	Significance	Confidence Interval
Bishop and Chiou (2004)	9	0.0001	0.0001	Yes	(0.0001, 0.0009)
Cai and Du (2011)	9	0.0805	0.0817	No	(−0.0020, 0.1654)
Chen and Hamori (2009)	10	0.1172	0.1208	Yes	(0.0630, 0.1786)
Fan et al (2010)	20	0.2101	0.2216	Yes	(0.1674, 0.2757)
Fu and Ren (2010)	15	0.0425	0.0433	Yes	(0.0171, 0.0694)
Giles et al (2008)	21	0.1191	0.1216	Yes	(0.0816, 0.1615)
Heckman and Li (2004)	2	0.1644	0.1646	No	(−0.1778, 0.5070)
Hu (2013)	18	0.1189	0.1210	Yes	(0.0861, 0.1559)
Huang et al (2002)	30	0.0925	0.0931	Yes	(0.0781, 0.1082)
Li (2003)	10	0.0779	0.0780	Yes	(0.0545, 0.1015)
Li, Liu, and Zhang (2012)	24	0.0881	0.0908	Yes	(0.0550, 0.1266)
Liu (1998)	3	0.0727	0.0730	No	(−0.0507, 0.1968)
Zhang et al. (2008)	32	0.0626	0.0628	Yes	(0.0522, 0.0734)
Messinis (2013)	15	0.0929	0.0931	Yes	(0.0757, 0.1104)
Messinis and Cheng (2009)	24	0.0658	0.0664	Yes	(0.0414, 0.0914)
Mishra and Smyth (2013)	9	0.1003	0.0971	Yes	(0.0495, 0.1448)
Ning (2010)	12	0.0753	0.0893	Yes	(0.0339, 0.1447)
Qian and Smyth (2008)	11	0.1648	0.1426	Yes	(0.0875, 0.1977)
Qin et al (2013)	4	0.0071	0.0071	No	(−0.0015, 0.0156)
Wang (2012)	20	0.1520	0.1475	Yes	(0.1043, 0.1907)
Xiu and Gunderson (2013)	88	0.1006	0.1008	Yes	(0.0903, 0.1114)
Yang and Mayston (2009)	9	0.0423	0.0424	No	(−0.0632, 0.1480)
Zhong (2011)	25	0.1345	0.1358	Yes	(0.1079, 0.1638)
Meng and Kidd (1997)	8	0.2084	0.2103	Yes	(0.1518, 0.2689)
Wang et al. (2014)	16	0.1114	0.1075	Yes	(0.0717, 0.1432)
Zhou (2014)	8	0.0155	0.0188	No	(−0.1162, 0.1537)
	452	0.1005	0.0547		

Table 2. Overview of Evidence Base by Clusters.

	Effect Size	Standard Error	Observations
Years of schooling	0.1831***	0.0057	527
Educational level	0.0998***	0.0038	452
College education and above	0.1388***	0.0058	205
Other education levels	0.06892***	0.0040	247

the level of income is reported by studies that examine the relationship between education level and income. We also find that college education and above is associated with a 13.88% increase in income, while other levels of education are associated with an approximately 6.89% increase in income. Overall, the evidence suggests that studies that use years of schooling as a measure of education report higher returns to education than studies that use education level dummies. Furthermore, we find that the returns to college education and above are higher than returns to other levels of education, thus supporting the argument of the college premium.

PET/FAT and PEESE results (genuine effect beyond bias)

Although the FEE and REE weighted means of the PCCs can be taken as valid descriptions of the overall evidence base, they may be subject to publication selection bias. Thus, we conduct a PET/FAT-PEESE analysis to examine whether the reported effect sizes are tainted with publication bias. We use the same cluster used for the REEs, that is, on the basis of education measure used. Table 3 Panel A presents the PET/FAT results with HLM estimations, while Table 3 Panel B presents the PEESE estimation results.

The PET/FAT results from Panel A suggest that the coefficient of the precision is positive and significant for all measures of education. However, there is evidence of publication selection bias in favour of studies that use education level dummies. This bias is severe considering that the constant terms in each of the three categories are greater than two in magnitude. Considering the evidence of genuine effect, we also report the PEESE results in Panel B to take account of the nonlinear association between the PCCs and their standard errors (Stanley and Doucouliagos 2007; Ugur 2013). The results from the PEESE are consistent with those from the PET/FAT analysis (i.e. the association remains positive although the magnitude of the coefficients changes).

The guidelines proposed by Cohen (1988), Doucouliagos and Ulubasoglu (2008) and Ugur (2013) indicate that a PCC represents large effect if

Table 3. PET/FAT results (Panel A).

	(1)	(2)	(3)	(4)
Variables	Years	Edu Level	College	Other Levels
Precision (β_0)	0.1803[a]	0.0445[a]	0.0364[a]	0.0442[a]
	(0.0120)	(0.0075)	(0.0109)	(0.0040)
Bias (α_0)	−0.0076	2.9925[b]	6.2209[a]	1.3624[c]
	(1.4118)	(1.2892)	(1.8546)	(0.7330)
Observations	527	452	205	247

Standard errors in parentheses
[a]$p < 0.01$,
[b]$p < 0.05$,
[c]$p < 0.1$.

Table 3. PEESE Results (Panel B).

Variables	(Edu Level)	(College)	(Other Levels)
Precision (β_0)	0.0537[a]	0.0581[a]	0.0472[a]
	(0.0069)	(0.0109)	(0.0037)
Standard error (α_0)	40.2685	27.5230	29.4916
	(43.2011)	(61.4665)	(28.8653)
Observations	452	205	247

Standard errors in parentheses
[a]$p < 0.01$,
[b]$p < 0.05$,
[c]$p < 0.1$.

its absolute value is greater than 0.4, medium effect if it is $0.1 \leq x < 0.4$ and small effect if it is less than 0.1. Based on these guidelines, we conclude that after controlling for selection bias, the returns to education in China are medium, given a 17.99% level of association between years of schooling and income. However, using education level, we find that the returns to education in China are small for all education levels but with evidence of publication selection bias. This evidence suggests that there is actually a predisposition to report higher returns for college education and above and to report lower returns for other levels of education. We note that without controlling for publication selectivity, studies reporting on the effects of college education and above on income tend to report relatively high returns. Specifically, we find that without controlling for selection bias, the returns to college education are approximately 13.88% which is about two times the returns to other levels of education (6.89%). However, after controlling for bias (PEESE results), the returns to college education is actually 5.81% and that of other levels of education is 4.72%.

Meta-regression results

As explained earlier, the PET/FAT analysis does not contain moderating variables and attributes potential bias only to publication selection. Thus, we conduct a multivariate MRA to understand the extent to which moderating variables explain variations in existing studies and whether the education-income relationship is robust to the inclusion of moderating variables. (Table 4) presents a summary statistics of the moderating variables used in the MRA.

The moderating variables are dummy variables which take the number ‘one’ if the estimate reported in the primary study is defined by the characteristic captured by the variable and zero if otherwise. The choices of moderating variables in the MRA are largely influenced by variations in primary studies which can potentially affect the effect sizes reported by each primary study. In addition, choices of moderating variables are also informed by empirical and theoretical assumptions made by the authors of the primary studies.

For instance, endogeneity of schooling has recently been argued as a problem that affects effect sizes (e.g. Card 1999; Lang 1993; Chen and Hamori 2009; Heckman and Li 2004; Li and Luo 2004). OLS estimates are biased and inconsistent in the presence of endogeneity. As such, the inference made from hypothesis tests can be misleading. The main source of endogeneity in the returns to education literature is the omission of an individual’s unobserved ability, which may affect both educational outcome as well as income. Another source of endogeneity may arise from measurement errors in the education variable, since, in some cases, information on schooling is provided in levels of education rather than years of education.

Some studies have argued that, because of a positive correlation between education levels and omitted ability, the return coefficient has an upward bias (e.g. Chen and Hamori 2009). Thus, to address the issue of endogeneity, some studies that examine returns to education in China control for endogeneity by using a set of exogenous instruments that are correlated with measures of education but not with the disturbance term. Studies such as Chen and Hamori (2009), Heckman and Li (2004), Li, Liu, and Zhang (2012), Wang (2012) and Mishra and Smyth (2013), among others, address endogeneity by conducting IV estimations in addition to or instead of the non-instrumented estimation like the OLS. Some of the common instruments used in the existing literature to account

Table 4. Summary Statistics Poverty MRA (Dummy Variables Are Divided by the SE of Precision).

Variable	Description	N	Mean	S.D.	Min	Max
t Value	t-statistic reported in primary studies	979	9.30	13.75	−10.34	288
Precision	Inverse of standard error of PCC	979	72.87	95.98	6.67	743.06
Male	Dummy = 1 if primary studies used data on males	979	45.44	44.41	0	298.51
IV	Dummy = 1 if primary studies used IV	979	7.22	19.88	0	106.11
Data period	Dummy = 1 if primary studies used data prior to 2000	979	21.81	37.05	0	180.12
Publication year	Dummy = 1 if primary studies is published after 2005	979	62.46	98.23	0	742.94
Journal	Dummy = 1 if primary studies is a journal paper	979	65.70	99.12	0	742.94
Journal rank	Dummy = 1 if primary studies is published in a high ranking journal	979	26.35	38.84	0	298.55
CHIP data	Dummy = 1 if primary studies used CHIP Data	979	33.13	46.73	0	180.12
CHNS data	Dummy = 1 if primary studies used CHNS Data	979	7.84	22.30	0	204.00
NBS data	Dummy = 1 if primary studies used NBS Data	979	4.69	16.29	0	298.51
Years of schooling	Dummy = 1 if primary studies used years of schooling as education measure	979	31.72	50.29	0	740.19
Urban	Dummy = 1 if primary studies focused on Urban China	979	43.36	42.02	0	298.51

for the endogeneity of education are quarter of birth, quarter of birth interacted with year of birth, parent's education level, spouse's education level and smoking behaviour. It is to be noted that the validity of most of these instruments is highly debatable and that they are often regarded as weak instruments.

Other approaches towards estimating returns to education include the Heckman two-step procedure (e.g. De Brauw and Rozelle 2008; Zhang et al. 2008; Kang and Peng 2012) and quantile regressions (e.g. Messinis 2013). In the current study, we control for studies that adopt IV estimation methods leaving out all other estimation methods such as the OLS, Heckman two-step and quantile regressions in the control category in order to establish whether there are significant differences in the estimates of returns to education based on the estimation methods applied.

Existing studies have shown that returns to education in China increase with time (e.g. Cai and Du 2011; Carnoy et al. 2012). Most of these studies indicate that the returns to education and wage in general increased dramatically in China sometime after the year 2000. This is evident from (Figure 1), which shows the relationship between return estimates and years of publication. Hence, we also control for data period to determine if these findings are consistent across the existing literature. We therefore use the year 2000 as the reference point and introduce a dummy for studies that use data prior to 2000 in order to capture possible variations in returns to education in the data period.

In addition, we control for publication type and publication year (i.e. whether studies were published after 2005). With regard to publication year, we examine the nature of reported effect sizes, given that recent studies often include larger datasets in their analysis. Specifically, we control for studies published after 2005, because we notice a significant increase in the number of publications after this date, and these include larger and richer datasets in their analysis. According to Gehr, Weiss, and Porzsolt (2006), empirical studies tend to report smaller effect sizes over time because of the use of larger datasets as well as falsification efforts that follow findings from preceding studies. Thus, with the surge in publications after 2005, we control for recently published studies to verify if the reported estimates become smaller over time.

With respect to publication type, we examine whether the effect sizes reported by journal publications are different from those that working papers report. This makes it possible to determine whether journal editors and authors are predisposed to publish papers with statistical significant estimates consistent with theory in order to justify the selected models (Card and Krueger 1995; Stanley 2008; Ugur 2013; Sterling, Rosenbaum, and Weinkam 1995). Additionally, we examine whether high-ranking journals produce systematically different results from low-ranking journals. Thus, we include a dummy to capture studies published in high-ranking[2] journals.

[2]The Australian Business Dean's Council (ABDC) and the Australian Research Council (ARC) present classifications for journal quality. Journals are ranked in descending order of quality as A*, A, B and C. Thus, we introduce a dummy for A*- and A-ranked journals (high quality) in our MRA and use other ranks as base.

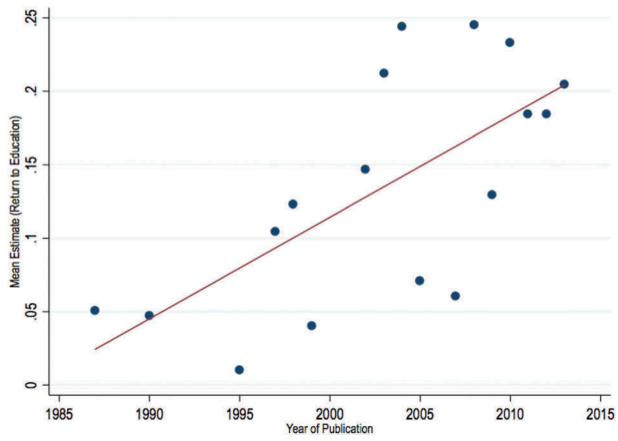

Figure 1. Relationship between return estimates and years of publication.

Another dimension specific to each study which can potentially affect reported effect sizes is the data source. In the existing literature, most studies use the CHIP data. Other sources of data which have been widely used in the literature include data from the Urban Survey Unit of the National Bureau of Statistics (NBS) and the CHNS. Various studies also use data from sources such as the China Urban Labor Survey (CULS) as well as primary data collected by authors or other institutions. With this heterogeneity in data source, it is worthwhile to examine whether the source of data affects the reported effect sizes. Therefore, we include dummies for studies that use the CHIP, NBS and CHNS dataset while omitting all other data sources in order to account for variations in reported estimates due to differences in data sources.

Besides, some studies examine returns to education in urban areas while others examine the same in rural areas. Other studies examine the returns to schooling by gender and examine how different returns to education might be for males compared to females. To determine whether returns to education in China differ based on location and gender, we control for studies that report on returns in urban areas and those that report on males.

Lastly, we control for years of schooling in the regression involving the entire sample. Controlling for years of schooling enables us to verify results retrieved from the PET/FAT analysis (i.e. whether studies that use years of schooling as a measure of education reported higher returns).

Table 5. MRA Results (weighted least square (WLS) estimations, with *t* values as dependent variable).

	(1)	(2)	(3)	(4)
Variables	Entire Dataset	Entire Dataset	Years of Schooling	Educational Level
Precision	0.1527[b]	0.1804[b]	0.1730[b]	0.1021[c]
	(0.0667)	(0.0735)	(0.0675)	(0.0565)
Journal rank	0.1003[a]	0.1074[a]	0.0996[a]	0.0785[a]
	(0.0305)	(0.0335)	(0.0348)	(0.0239)
IV	0.0695[a]	0.0729[a]	0.0645[a]	0.0061
	(0.0161)	(0.0180)	(0.0156)	(0.0174)
Data period[d]	−0.0760[a]	−0.0747[a]	−0.1065[a]	−0.0266
	(0.0114)	(0.0128)	(0.0127)	(0.0173)
Publication year[e]	−0.0345[b]	−0.0467[b]	−0.0362[c]	0.0050
	(0.0157)	(0.0183)	(0.0191)	(0.0299)
Journal	−0.0504	−0.0650	−0.0041	−0.0627
	(0.0552)	(0.0608)	(0.0532)	(0.0497)
CHIP dataset	0.0115	0.0436	0.0917[b]	−0.0485[b]
	(0.0289)	(0.0314)	(0.0359)	(0.0189)
CHNS dataset	−0.0911[a]	−0.0167	−0.0854[a]	−0.0069
	(0.0234)	(0.0255)	(0.0228)	(0.0744)
NBS dataset	0.6649[a]	0.7199[a]	0.7358[a]	0.0195
	(0.0436)	(0.0481)	(0.0454)	(0.0772)
Years of schooling	0.0906[a]			
	(0.0055)			
Urban	0.0373	0.0336	0.0201	0.0831[a]
	(0.0244)	(0.0270)	(0.0243)	(0.0184)
Male	−0.0221	−0.0194	−0.0229	−0.0624[b]
	(0.0202)	(0.0227)	(0.0230)	(0.0273)
Constant	−8.0414[a]	−7.8167[a]	−7.6622[a]	−1.5003
	(1.6517)	(1.7828)	(2.1295)	(1.4682)
Observations	979	979	527	452
Number of groups	59	59	48	26

Standard errors in parentheses
[a]$p < 0.01$,
[b]$p < 0.05$,
[c]$p < 0.1$.
[d]Dummy for pre-2000 data.
[e]Dummy for 2005 publications and beyond.

To capture all the discussed dimensions of primary studies, we estimate Model (9) with HLM and present the results in (Table 5). This estimation method allows for the control of variations within and between each study, given that some primary studies present more than one estimate.

From Panel 1 of (Table 5) (entire dataset), after controlling for all relevant moderating variables, we note that the coefficient of precision is 15.27%, while for the years of schooling (Panel 3) and education level sample (Panel 4), the coefficients of precision are 17.30% and 10.21%, respectively. We observe that in the specification in which we do not include the ‘years of schooling’ dummy (Panel 2 Table 5), the coefficient of precision is 18.04%. The dummy for studies that report estimates for years of schooling in Panel 1 is positive and significant. These results suggest that, even after controlling for the moderating variables, the studies using 'years of schooling' tend to report higher returns than studies using other measures of schooling, such a level of education dummies.

The results from the MRA also indicate that studies that use various IV approaches compared to other estimation methods tend to report marginally higher returns to education in China. This is consistent with the findings of most studies.

For publication year, we find that, consistent with Gehr, Weiss, and Porzsolt (2006) assertion, studies published after 2005 tend to report smaller effect sizes. Thus, the effect sizes for returns to education reported by recent studies are smaller compared to studies published prior to 2005. However, this is not the case for studies that report estimates using educational level as the measure of education, as the coefficient here is not significant. Similarly, results indicate that studies that use relatively older datasets (i.e. before 2000) tend to report weaker returns to education. This supports existing arguments that suggest that returns to education in China increase over time (Heckman and Li 2004; Li 2003; Li, Liu, and Zhang 2012; Zhang et al. 2005; Mishra and Smyth 2013).

We further find that there is a significant bias associated with publication outlets used. In this regard, higher ranked journals tend to systematically report high returns to education in China. The publication type, however, is not significant. Thus, the effect sizes reported by studies published both in journals and as working papers are not systematically different.

With regard to the dataset used by primary studies, we find that studies that use the NBS dataset tend to report higher returns to education, whereas those that report estimates using CHNS data report relatively low returns to education.

We find that the dummy for studies that report estimates using data on urban areas is mainly insignificant across our regressions. However, from Panel 4, we note that in the educational level only data, studies that use data on urban areas tend to report relatively higher returns to schooling for urban areas than for rural areas. Similarly, from Panel 4, the results indicate that returns to education for males are relatively lower than for females.

We now turn to some specific research choices or research practices often adopted in the returns to education in China literature. We zoom into various specific dimensions of the research fields and examine what the conditional effect of education on income is for studies that adopt these research practices. First, we focus on studies that use IV techniques to examine the returns to education in China, using the CHIP dataset. For this category of studies, the returns to education are estimated to be 17.94%. Secondly, we examine studies that focus on urban areas with data before the year 2000 and apply IV techniques in their analysis. In this case, we find that the conditional effect of education on income is 9.19%. Thirdly, we note that the return to education is approximately 18.95% for studies that use years of schooling as the measure of education while analysing CHNS data. Lastly, we examine the conditional effect of education on income for studies published in the last decade (2005 and beyond) and apply IV techniques in their estimations. The returns to education for this category is 9.34%.

VI. Summary and conclusion

We set out to examine the returns to education in China using meta-analysis. With meta-analysis, we evaluate and synthesize the effect-size estimates on returns to education in China, taking into account heterogeneity and controlling for publication selection bias.

The PET/FAT and PEESE results indicate that returns on an additional year of schooling are associated with a 17.99% increase in income beyond publication selection bias. Lower returns are observed for studies that report on the association between various education levels and income. Furthermore, considering education levels, the PEESE results suggest that higher returns are associated with college education relative to other levels of education. Specifically, we note from the PEESE results that returns to college education and other levels of education are 5.81% and 4.72%, respectively. The PET/FAT and PEESE results also suggest that studies that use years of schooling as the measure of education report higher returns than those that use education level, and this is consistent with the findings from our MRA. We also note that variations in reported results are largely influenced by study characteristics such as estimation methodology, dataset used and measure of education used, among others.

Lastly, we identify a number of issues that present avenues for future research. We note that a number of studies on the subject exist in the Chinese language, but owing to language barriers, we are not able to include such studies in our meta-analysis. In this regard, it is worthwhile to conduct a separate meta-analysis that considers studies written in the Chinese language. In addition, relatively few studies examine the effect of education on firm productivity in China. An increase in the number of primary studies that examine this relationship would provide further insight and possibly provide a wider evidence base for a meta-analysis in the future.

Disclosure statement

No potential conflict of interest was reported by the authors.

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