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Returns to Education in China: A Meta-analysis

Sefa Awaworyi[1] and Vinod Mishra[2]

Abstract

Within labour economics, returns to education is an area of focused research. Moreover, amongst the studies looking at the emerging economies, China is the most widely studied economy. While there is general consensus that returns to education are positive, studies use various datasets and methodologies, and consequently present varying estimates of the returns to education. We perform a meta-analysis of the estimates of the returns to education in China, which addresses issues of heterogeneity in the existing literature and examines if variations in reported estimates could be explained by study characteristics such as dataset and estimation methods amongst others. After controlling for publication selection bias, precision effect and funnel asymmetry test (PET/FAT) results indicate that an additional year of schooling is associated with 17.26% increase in income. Meta-regression analysis (MRA) results show that moderating variables and study characteristics account for 53.92% of variations in reported estimates. After controlling for moderating variables, MRA results suggest that the association between education and income in China is 10.25%.

Keywords: Schooling, Earnings, China, Meta-analysis

[1]Corresponding Author Department of Economics Monash University, VIC – 3800, Australia
Email: sefa.awaworyi@monash.edu

[2] Department of Economics Monash University, VIC – 3800, Australia Email: vinod.mishra@monash.edu

1. Introduction

Education has an important role in transforming a nation's living standards. The educational outcomes are directly linked to labour market productivity and human capital accumulation, which 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, the returns to education vary significantly between nations and across time periods. This variation is even bigger in the 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 look at, the biggest challenges come in terms of collecting the data, choosing a methodology and in controlling all the other observable and non-observable characteristics that may have a direct or indirect effect on the education-earning relationship. Most of the earlier studies focussed on a Mincer (1974) type of model specification to estimate the returns to education by using Ordinary Least Squares Methodology (OLS). Later studies pointed out that both the educational outcomes and earning are affected by the unobserved skills of a person, thereby creating the problem of endogeneity in the education-earnings relationship. These studies suggested the use of instrumental variables (IV) to correct for this bias using a Two Stage Least Squares Approach (2SLS). One of the problems in going ahead with 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.) can be argued as not meeting 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 look at the returns to education in Chinese context. There are several reasons for focussing on China in particular. First, the returns to 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 is 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 finding out more about the role of education in facilitating this transition. Third, it is important to understand the sources of variations (such as datasets, methodology, choice of instruments, time period of study etc.) in the returns to education that are reported in existing studies and have a unified understanding of the role played by education in the Chinese context.

To the best of our knowledge, except for Fleisher et al. (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 studies used in Fleisher et al. (2005b) and Liu and Zhang (2013), the results of this study is not a duplication of findings presented by both studies. Fleisher et al. (2005b), compare the growth rate in returns to education in Central and Eastern Europe, China and Russia. Thus, 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 thus, is particularly similar to our study. We find a number of limitations with these studies and thus address them in this current study. First, both studies do not account for heterogeneity in the existing literature, which would make it possible to accurately compare estimates from different studies. This is important given that various studies that examine the returns to education in China draw on evidence from various datasets and estimation methods. To address this, we calculate partial correlation coefficients (PCCs) for each effect size in order to allow for study comparisons. Second, both studies do not control 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 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). Thus, we fill this gap by providing evidence of the effect of education on income in China beyond publication selection bias. Lastly, since Fleisher et al. (2005b), there has been a significant increase in the literature that examines the returns to education in China and most of these studies are conducted with newer datasets. Thus, given the recent trends which suggest that returns to education in China increases over time, it is worthwhile to adopt appropriate and comprehensive techniques to examine the existing empirical literature on this phenomena. This would help draw a general conclusion on the overall evidence that examines returns to education in China.

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

2. Brief Overview of the Literature

Since the seminal work of Mincer (1974), examining the returns to education has been an important part of economics literature. However, the focus on Chinese data pioneered in the

1990s. Based on Mincerian models, several studies provide evidence which suggests that the returns to education in China have increased in the last two decades and now approaches 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 returns to education in China literature.

To begin with, the 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 return to education with an average of about 2.0% to 4.5% in most studies. Using 1986 data, 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, Knight and Song, 1993, Knight and Song, 1995, Gustafsson and Li, 2000) use 1980s data either from the Chinese Household Income Project (CHIP) or the Urban Household Income Surveys (UHIS) and provide evidence of low returns to education. When Gustafsson and Li (2000) compare results from a 1988 sample with 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 the returns to education in China (Heckman and Li, 2004, Li, 2003, Li et al., 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 a 2000 data from Chengdu and report the returns to education to be 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 in the context of a meta-analysis what the general conclusion would be in terms of returns to education in China over time.

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. An exception is Chen and Hamori (2009) and Ren and Miller (2012a), where slightly higher returns for males were reported based on a recent sample 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 four-year college education compared 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 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.

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 use rural data and/or compare returns in rural with 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 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 gradually shifts to 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 instrumental variable (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, issues concerning the endogenous bias of education have often been argued (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 instrumental variable (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). The commonly used instruments for education include parental education, spouse's education, number of siblings and parental income amongst 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.

3. Data

The data used in this study is 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 (MAER-NET), which reflect transparency and best practices in meta-analyses (Stanley et al. (2013)). We adopt a three-staged search strategy in order to identify relevant and reliable empirical literature for our review. The first step is to identify relevant electronic databases from which to search and also relevant keywords related to education and income. Second, is to conduct the electronic database search after which results are uploaded into a reference manager for screening. The last stage involves a manual search process of relevant websites.

Overall, we searched in 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. After managing duplicates, 984 studies were identified to be reviewed for inclusion or exclusion in our study. The study screening process was in two stages. At the first stage of screening, we reviewed the titles and abstracts of studies. At this point we examined if the study focused on China and whether or not the independent variable was education. The 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 relevance to our research question. The full-text screening led to the inclusion of 53 empirical studies that reported on returns to education.

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 or the other form of the following Mincer (1974) equation:

$$y_i = \alpha + \beta_1 Edu_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \beta_4 X_i + \epsilon_i$$

such that Edu_i is the years of education or the dummies for education levels, Exp_i is the experience and Exp_i^2 is the squared-experience, 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 is 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 findings in different meta-analysis (De Dominicis et al., 2008, Stanley, 2008, Stanley et al., 2009).

4. Meta-analysis Tools and Methods

We adopt five main meta-analysis tools in reviewing the returns to education in China literature. 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 (see,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 for 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 in each category. Fourth, we conduct precision effect tests (PETs) and funnel asymmetry tests (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 which allow us to control for and determine the effects of various moderating variables.

4.1.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 degrees of freedom and t-statistics 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 FEEs 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 et al., 2009). We calculate the FEEs weighted means based on the approach adopted by Stanley and Doucouliagos (2007), Stanley (2008), De Dominicis et al. (2008) and Ugur (2013) amongst others. They report that the FEEs can be calculated using equation (3).

$$\bar{X}_{FEE} = \frac{\sum r_i\,(1/se_{ri}^2)}{\sum 1/se_{ri}^2} \qquad (3)$$

Where $\bar{X}_{FEE}$ 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 subject to publication selection bias, they are only taken as descriptive summary of the evidence base and not as measures of genuine effect (De Dominicis et al., 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 (5) is used to calculate the REE weighted means.

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

Where $\bar{X}_{REE}$ and σ^2 is 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 distributes 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 et al., 2009, Hawkes and Ugur, 2012).

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

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

Here all variables remain as explained above and t_i is the t-statistic extracted from the primary studies. $1/se_{ri}$, 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)

$$r_i = \beta_0 + \alpha_0(se_{ri}^2) + u_i \tag{6}$$

We divide through equation (6) by se_{ri} to obtain equation (7) in order to address heteroskedasticity concerns.

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

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, they assume that moderating variables related to each study or capturing 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 meta-regression analysis (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 et al. (2011) and Ugur (2013).

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

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 independency amongst reported estimates can be questioned (De Dominicis et al., 2008). Thus, we account for this multi-level structure and its implied dependence by estimating the following equation;

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

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 $\epsilon_i \sim N(0, SE_{ri}^2)$, where SE_{ri}^2 is the square of the standard errors associated with each of the derived PCC, and $u_i \sim N(0, \tau^2)$, where τ^2 is the estimated between-study variance.

5. Results

5.1.Fixed Effect Weighted Means (Overview of Evidence Base)

Tables 1a and 1b 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, 44 primary studies with a total of 469 estimates use years of schooling as the measure of education. Results indicate that from the 44 primary studies only eight studies

(18.18% of the total studies) with 39 estimates (8.32% 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 the returns to education in China are positive as expected.

[INSERT TABLE 1A HERE]

From table 1b, we note that 24 primary studies with 428 estimates report on the association between various education levels and income. We find that 5 studies (20.83% of the total primary studies) with 27 estimates (6.31%) 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.

[INSERT TABLE 1B HERE]

Overall, without addressing heterogeneity or any potential issues concerning selection bias, the existing 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.

5.2.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.

[INSERT TABLE 2 HERE]

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, results indicate that an additional year of schooling is associated with a 17.96% increase in income. Similarly, an average of a 10.10% increase in 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 14.04% increase in income while other levels of education are associated with approximately 7.07% increase in income. Overall, 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.

5.3.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 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. Panel A of table 3 presents the PET/FAT results with cluster-robust standard errors. Panel B presents the PEESE estimation results also with cluster-robust standard errors.

[INSERT TABLE 3 HERE]

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 bias for studies reporting estimates for education level, we report the PEESE results in Panel B for these categories 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 however, the magnitude of the coefficients changed).

Guidelines proposed by Cohen (1988), Doucouliagos and Ulubasoglu (2008) and Ugur (2013) indicate that a PCC represents large effect if 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 17.26% 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. We however note that after controlling for bias, the returns to other levels of education is about 1.99% higher than the returns to college education and above. This is evident considering the precision's coefficient for college education and above and other levels of education which is 0.06 and 0.08 respectively. We also note that without controlling for bias, 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 14.04% which is about two times the returns to other levels of education (7.07%). However, evidence suggests that there is actually a predisposition to report higher returns for college education and above and lower returns for other levels of education. Results show that after controlling for bias, the returns to college education is actually 6.3% and other levels of education 8.29%.

5.4.Meta-regression Results

As explained earlier, PET/FAT analysis do not contain moderating variables and attribute 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 moderating variables used in the MRA.

[INSERT TABLE 4 HERE]

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 authors of primary studies. For instance, endogeneity of schooling have recently been argued as a problem that affects effect-sizes (see, eg., 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, 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 the educational outcomes as well as income. Another source of the 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 (see, 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 et al. (2012), Wang (2012) and Mishra and Smyth (2013) amongst others, address endogeneity by conducting instrumental variable (IV) estimations in addition to or instead of the non-instrumented estimation like the ordinary least square (OLS). Some of the common instruments used in the existing literature to instrument for one's own 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 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) and Kang and Peng (2012)) and quantile regressions (e.g., (Messinis (2013)). In the current study, we control for OLS and IV estimation methods leaving out all other estimation methods such as the Heckman two-step and quantile regressions as the control category in order to establish if 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 have 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 note that about 60.2% of estimates reported use data ranging from 2000 to 2010. 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 that the data period has on returns to education.

[INSERT FIGURE 1 HERE]

In addition, we control for publication type and publication year (i.e. whether studies were published after 2005). With regards 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. In fact, approximately 80.26% of estimates reported come from studies published after 2005. According to Gehr et al. (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 effect-sizes reported by journal publication are different from what 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 to justify selected models (Card and Krueger, 1995, Stanley, 2008, Ugur, 2013, Sterling et al., 1995).

Another dimension specific to each research which can potentially affect reported effect-sizes is the data source. In the existing literature, most studies use the Chinese Household Income Project (CHIP) data. Other sources of data which have been widely used in the literature include data from the National Bureau of Statistics (NBS) and the Chinese Household National Survey (CHNS). Various studies also use data from sources such as the China Urban Labor Survey (CULS) and also 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 effect-sizes reported. Therefore, we include dummies for studies that use CHIP, NBS and CHNS dataset while omitting all other data sources in order to account for variations in reported estimates due to difference in data sources.

Besides, some studies examine returns to education in urban areas while others examine rural areas. To determine whether returns to education in China differ based on location, we control for studies that report on returns in urban areas.

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).

To capture all the discussed dimensions of primary studies, we estimate model (9) with cluster-robust standard errors and present results in table 5. This estimation method allows for the control of variations within each study given that some primary studies present more than one estimate.

[INSERT TABLE 5 HERE]

Based on the results from table 5, we observe that the returns to education in China are robust to the inclusion of moderating variables given that the coefficients of the precision across all panels are positive and significant. From panel 1 of table 5 (entire dataset), we find that moderating variables and study characteristics account for 53.92% of variations reported in estimates of returns to education in China. For studies that use only years of schooling (panel 2 table 5), moderating variables account for 63.55% of variations and for studies that use educational level (panel 3 table 5), moderating variables account for 32.83% of variations in estimates. For the entire dataset, after controlling for moderating variables, we note that the returns to education in China is 10.25% while for the years of schooling and education level sample, returns are approximately 20.77% and 8.03%, respectively. We observe that in the specification in which we do not include the "years of schooling" dummy (panel 2 table 5), the returns to education are roughly 11%, which is mid-way between the returns to education obtained by studies using only years of education and the studies using education level only. 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 lower returns to education in China. This is consistent with the findings of Li et al. (2012).

For publication year, we find that consistent with Gehr et al. (2006)'s 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. We however find that there is no bias associated with publication outlets used. Thus, the effect sizes reported by both studies published in journal and working papers are not systematically different. We also find that studies that use NBS dataset tend to report higher returns to education compared to others that use data from CHNS, CHIP and from other sources.

Lastly, the results from the MRA support those from our PET/FAT analysis which suggests that studies that use years of schooling as the measure of education tend to report higher returns to education than studies that use education level. Furthermore, we note that studies that report on the returns to education in urban areas in China report higher returns than studies that report on rural areas.

6. 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.

PET/FAT and PEESE results indicate that return on an additional year of schooling is associated with 17.26% 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, PET/FAT and PEESE results suggest that lower 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 6.3% and 8.29%, 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.

Overall, after controlling for moderating variables, MRA results suggest that the return to education in China is 10.25%. We also note that variations in reported results are largely influenced by study characteristics such as estimation methodology, dataset used and also the measure of education used amongst other things.

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; however, 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.

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Tables

Table 1A: Years of Schooling and Income
(Overview of Evidence Base per Study - Simple & 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		
Fan 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 et al (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 (2012)	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 (1995)	3	0.0371	0.0371	No	(-0.0539, 0.1281)
Total	469				

Table 1B: Educational Level and Income
(Overview of Evidence Base per Study - Simple & 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 et al (2012)	24	0.0881	0.0908	Yes	(0.0550, 0.1266)
Liu (1998)	3	0.0727	0.0730	No	(-0.0507, 0.1968)
Luo (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)
	428	0.1017	0.0552		

Table 2: Overview of Evidence Base by Clusters

	Effect Size	Standard Error	Observations
Years of Schooling	0.1796***	0.0062	469
Educational Level	0.1010***	0.0038	428
College Education and Above	0.1404***	0.0061	187
Other Education Levels	0.0707***	0.0037	241

Table 3 Panel A: PET with Robust Standard Errors

VARIABLES	(Years)	(Edu Level)	(College)	(Other Levels)
Precision (β_0)	0.1726***	0.0406***	0.0363***	0.0658***
	(0.0108)	(0.0032)	(0.0060)	(0.0051)
Bias (α_0)	0.6879	3.8407***	6.5521***	4.5573***
	(0.9116)	(0.5068)	(0.7348)	(0.6459)
Observations	469	428	187	710
R-squared	0.3529	0.2740	0.1654	0.1884

Table 3 Panel B: PEESE with Robust Standard Errors

VARIABLES	(Edu Level)	(College)	(Other Levels)
Precision (β_0)	0.0513***	0.0630***	0.0829***
	(0.0028)	(0.0054)	(0.0044)
Standard Error (α_0)	86.2602***	123.2545***	69.3367***
	(18.3480)	(26.4778)	(18.9301)
Observations	428	187	710
R-squared	0.5033	0.5355	0.3825

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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	897	9.47	14.18	-8.29	288
Precision	Inverse of Standard Error of PCC	897	75.77	99.66	6.67	743.06
OLS	Dummy=1 if primary studies used OLS	897	47.37	46.39	0	298.51
IV	Dummy=1 if primary studies used IV	897	6.35	19.45	0	106.11
Data Period	Dummy=1 if primary studies used data prior to 2000	897	23.26	38.16	0	180.12
Publication Year	Dummy=1 if primary studies is published after 2005	897	64.41	102.29	0	742.94
Journal	Dummy=1 if primary studies is a journal paper	897	69.44	102.39	0	742.94
CHIP Data	Dummy=1 if primary studies used CHIP Data	897	35.65	47.92	0	180.12
CHNS Data	Dummy=1 if primary studies used CHNS Data	897	8.29	23.03	0	204.00
NBS Data	Dummy=1 if primary studies used NBS Data	897	5.11	16.95	0	298.51
Years of Schooling	Dummy=1 if primary studies used years of schooling as education measure	897	31.81	52.01	0	740.19
Urban	Dummy=1 if primary studies focused on Urban China	897	44.62	43.03	0	298.51

Table 5: MRA Results with Heteroskedasticity Robust Standard Errors (WLS estimations, with *t* values as dependent variable)

	(1)	(2)	(3)	(4)
VARIABLES	Entire Dataset	Entire Dataset	Years of schooling	Educational Level
Precision	0.1025***	0.1186***	0.2077***	0.0803***
	(0.0266)	(0.0293)	(0.0417)	(0.0279)
OLS	0.0293	0.0153	0.0233	0.0112
	(0.0220)	(0.0210)	(0.0312)	(0.0186)
IV	-0.0362*	-0.0456**	-0.0675**	-0.0099
	(0.0191)	(0.0184)	(0.0288)	(0.0193)
Data Period^	-0.0262	0.0004	-0.0566	-0.0093
	(0.0201)	(0.0201)	(0.0373)	(0.0084)
Publication Year#	-0.0464**	-0.0428**	-0.0618*	-0.0355**
	(0.0183)	(0.0205)	(0.0316)	(0.0157)
Journal	-0.0120	-0.0193	-0.0114	-0.0043
	(0.0146)	(0.0150)	(0.0238)	(0.0188)
CHIP Dataset	-0.0003	0.0317**	0.0599**	-0.0239
	(0.0161)	(0.0154)	(0.0268)	(0.0172)
CHNS Dataset	-0.0353*	0.0454**	-0.0149	-0.0142
	(0.0194)	(0.0208)	(0.0238)	(0.0227)
NBS Dataset	0.2984**	0.3750**	0.3883***	-0.0126
	(0.1494)	(0.1648)	(0.1475)	(0.0211)
Years of Schooling	0.1015***			
	(0.0158)			
Urban	0.0496***	0.0419**	0.0283	0.0477***
	(0.0171)	(0.0186)	(0.0296)	(0.0147)
Constant	-1.6964	-1.1583	-1.8284	1.6401**
	(2.0204)	(2.1283)	(2.3386)	(0.6451)
Observations	897	897	469	428
R-squared	0.5392	0.4314	0.6355	0.3283

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

^ Dummy for Pre 2000 Data

#Dummy for 2005 Publications and Beyond

Figure 1