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Benos, Nikos and Zotou, Stefania

University of Ioannina

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Nikos Benos[a,b*] and Stefania Zotou[a**]

University of Ioannina, Ioannina, Greece

[*]Corresponding author: Nikos Benos, Tel: +30-2651005955, Fax: +30-2651005092, E-mail: nbenos@cc.uoi.gr.
[**] E-mail: stefaniazotou@gmail.com.
[a] Department of Economics, University of Ioannina, University Campus, P.O. Box 1186, 45110 Ioannina, Greece,
[b] Laboratory of Applied Economics and Social Policy (LAESP), University of Ioannina, University Campus, P.O. Box 1186, 45110 Ioannina, Greece.

Abstract

This paper surveys the literature that examines the effect of education on economic growth. Specifically, we apply meta-regression analysis to 56 studies with 979 estimates and show that there is substantial publication selection bias towards a positive impact of education on growth. Once we account for this, we find evidence of a genuine effect of education on economic growth. The variation in reported estimates can be attributed to differences in the measurement of education and study characteristics, most importantly model specification, estimation methodology, type of data and the research outlet where studies were published, e.g. academic journals vs. working papers.

JEL Classification: I25, E24, C01, O50

Key words: Education, human capital, economic growth, meta-regression analysis, world sample

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1. INTRODUCTION

The importance of human capital for economic growth has been an extremely debated topic. Following Schultz (1961) and Becker (1964), we define human capital as the set of knowledge, skills, competencies and abilities embodied in individuals and acquired through education, training and experience. Education is considered as one of the most significant human capital investments. It plays a vital role in the process of economic growth and a significant amount of research has been devoted to study the education-growth nexus.

From a theoretical point of view, there is an important distinction between neo-classical and endogenous growth theories regarding the linkage between human capital and economic growth. The former argue that a one-off permanent increase in the stock of human capital results in a one-off increase in the economy's growth rate. On the contrary, new growth theories argue that the same one-off increase in human capital causes a permanent increase in growth. The social benefits of education are much greater in the latter case (Sianesi and Van Reenen, 2003).

Theoretical contributions emphasize different mechanisms through which education affects economic growth. First, education increases the human capital of the labor force, which increases labor productivity and transitional growth towards a higher equilibrium output level. Second, in endogenous growth theories, education increases the innovative capacity of the economy, knowledge of new technologies, products and processes and thus promotes growth (Hanushek and Woessmann, 2008).

From an empirical point of view, the macroeconomic literature on the relationship between human capital and economic growth attempts to test empirically different model specifications. Usually, these empirical approaches employ cross-section data. Other studies adopt time-series analysis for small groups of countries (e.g. OECD), where data quality is better. Finally, some research combines cross-section data with time-series information using panel datasets. However, the impact of human capital on economic growth remains controversial, due to a number of conceptual and methodological problems, such as the measurement of human capital and growth, as well as differences in parameters across countries or regions.

This study surveys the empirical literature on the education-economic growth relationship. Three main categories of empirical approaches are distinguished: those that refer to cross-section, those that use panel data and those that employ time-series. The first category attempts to explain cross-section (e.g. country) differences in growth, while the second one examines both the cross-section growth differences as well as the performance over time in each cross-section. The third category focuses on country-specific growth experiences.

Given the diversity of findings on the link between education and growth, we conduct meta-regression analysis (MRA). MRA is a subset of meta-analysis. Meta-analysis combines and integrates the results of several studies that share a common aspect so as to be combinable in a statistical manner (Harmon et al, 2003). MRA is a quantitative literature review of the estimates obtained from previous regression analyses and attempts to explain the variation in their results (Stanley and Jarrell, 1989). It aims at explaining the excess study-to-study variation typically found in empirical results and investigates the presence of publication selection bias (Stanley, 2005). Publication bias arises when editors, reviewers and researchers prefer to report findings, which are statistically significant and/or satisfy certain theoretical expectations (Doucouliagos, 2005, Stanley, 2008). As a result, it biases the literature's average reported effect away from zero. An additional advantage of MRA is that it allows the researcher to include aggregate data, e.g. data on aggregate labor supply that can not be included in individual studies (Groot and Maassen van den Brink, 2000). MRA allows us to examine factors that are likely to explain the heterogeneity of findings in the education-economic growth literature and the potential impact of study characteristics on the estimated relationship between education and growth.

As a consequence, we provide evidence that different measures of education give rise to different coefficients of the size effect of education on growth. Moreover, the variation in empirical estimates can be partially explained by the type of data, model specification, estimation methodology, and whether a particular study has been published or not in an academic journal, a journal listed in the "best" journals listed in Mamuneas et al (2010) and ESA (Economic Society of Australia, 2008).[1]

The rest of the paper is organized as follows. Section 2 reviews the main empirical studies concerning the role of education as a form of human capital in economic growth. Section 3 presents the most important proxies used to measure education and economic growth. Section 4 presents the construction methodology of our meta-data set, section 5 describes the different meta-analysis estimation methods employed and section 6 analyzes the meta-regression results. Finally, section 7 summarizes our main findings and concludes.

2. REVIEW OF THE LITERATURE

The literature started with cross-section studies. Two of the earliest works have been those by Romer (1989), and Azariadis and Drazen (1990), who find via OLS and IV (Instrumental Variables), that literacy is positively associated with growth. Barro (1991) shows through OLS, that per capita GDP growth is positively related to enrollment and literacy rates and negatively associated with student-teacher ratios. Murphy, Shleifer and Vishny (1991) employ OLS and report a positive growth impact of primary enrollment rates, while they find that enrollments in engineering and law are positively and negatively associated with growth respectively. Applying Extreme Bounds Analysis (EBA), Levine and Renelt (1992) also suggest a positive effect of enrollment rates on per-capita GDP growth, while Mankiw, Romer and Weil (1992) using OLS find the same impact regarding the percentage of the working-age population in secondary school. However, Benhabib and Spiegel (1994) employ OLS and find that human capital does not affect per capita growth. Employing regression tree analysis, Durlauf and Johnson (1995) show that the fraction of the working-age population enrolled in secondary school has a positive effect on GDP growth only for the intermediate income country group with low human capital and for the high income group of countries. Moreover, Lee and Lee (1995) via OLS and IV, report a positive influence of test scores on GDP per worker growth, but this is not true for literacy and enrollment rates, as well as student-teacher ratios. Applying 3SLS, Gemmell (1996) concludes that per capita growth rates are positively associated with enrollment rates, while Collins and Bosworth (1996) find the same relationship using schooling years through OLS. On the contrary, Bloom et al (1998) and Temple (1999) report an insignificant effect of schooling years on growth via OLS. However, Temple finds a positive impact of schooling on growth applying least trimmed squares.

Furthermore, Hanushek and Kimko (2000), through OLS, show that schooling years and scores are strongly positively related to growth, while Bils and Klenow (2000) report such an influence with respect to enrollment rates and schooling years. Employing OLS, Ranis, Stewart and Ramirez (2000) find a positive effect of literacy on growth, while Krueger and Lindahl (2001) show that the change in schooling years has little effect on growth, when the growth equation is estimated with high frequency changes (i.e. five years), but a strong positive effect over periods of ten or twenty years. Using semiparametric estimation, Kalaitzidakis et al (2001) find nonlinear effects of schooling years, but not enrollment rates, on growth, while Pritchett (2001), employing OLS and IV, reports a negative growth influence of schooling years. Moreover, Knowles et al (2002) show using OLS and 2SLS that female and male schooling years have a positive and negative impact on growth respectively. Furthermore, Bosworth and Collins (2003) find a stronger positive correlation between growth and the initial level of schooling years than between growth and change in schooling, as well as a positive correlation with scores via OLS. In a nonlinear framework, Papageorgiou (2003) employs OLS as well as IV and provides evidence for a positive role of schooling years on growth. Chakraborty (2004) shows via OLS that enrollment rates increase growth, but Barro and Sala-i-Martin (2004) through 3SLS, show that schooling years are insignificantly related to per-capita growth rates, while scores exert a highly significant positive impact on growth. Finally, Lee (2010) reports an insignificant impact of enrollment rates on growth.

Panel data analysis became common later then cross-section analysis mainly due to the availability of more complete data sets. In this framework, Barro (1996), as well as Bassanini and Scarpetta (2001) applying 3SLS and the Pooled Mean Group (PMG) estimators respectively, find that per capita growth rates are positively associated with schooling years. Barro (2001) shows via 3SLS that scores and schooling years have a strong positive relation with per capita GDP growth, whereas Appiah and McMahon (2002) show that the per capita growth effects of enrollment rates are not significant. Furthermore, Gyimah-Brempong et al (2006) using the Arellano-Bond dynamic panel data estimator, find that schooling years have a positive effect on per capita growth. Via Pooled Least Squares (PLS), Keller (2006) shows that enrollment rates and primary education expenditure contribute highly significantly to GDP per capita growth. Using Feasible Generalized Least Squares (FGLS), Siddiqui (2006) finds that schooling years exert an insignificant impact on growth, whereas female and male education growth rates affect growth significantly (positively and negatively respectively).

By employing a seemingly unrelated regression, Bose et al (2007) find a negative effect of enrollment rates on GDP per capita growth, whereas Hanushek et al (2007) by maximum likelihood using the HLM (Hierarchical Linear Modeling) algorithm, show that the quantity of schooling (schooling years) has a strong positive effect on growth that is substantially reduced once quality (test scores) is considered. Using a new data set for schooling years, Cohen and Soto (2007) show that in standard growth regressions, their GMM and fixed effects estimates of schooling are positive. Sterlacchini (2008) employs OLS in nonlinear specifications and reports a positive growth effect of the population share with tertiary education. Applying LSDV, FGLS, 2SLS and GMM, Baldacci el al (2008) find that both the level and changes in enrollment rates are positively related to growth. In addition, Hanushek and Woessmann (2008) using added-variable techniques, find that scores and schooling years feature a positive effect on GDP per capita growth.

Costantini and Monni (2008) find via 3SLS a positive relationship between enrollment rates and growth, while Bhattacharyya (2009) employing 2SLS and Seetanah (2009) via GMM report also a positive growth effect of schooling years and enrollment rates respectively. Sandar and Macdonald (2009) applying GMM, as well as Chen and Gupta (2009) through pooled OLS and GLS, provide controversial results regarding the growth impact of enrollment rates. Conducting fixed-effects and system-GMM estimations, Lee and Kim (2009) suggest that while secondary education enrollment rates appear important for low-income countries' growth, higher education is growth-enhancing for upper middle and high-income countries. Benos and Karagiannis (2010) show that enrollment rates have a positive effect on GDP per capita growth, while student-teacher ratios exert a negative influence via GLS and GMM. Tsai et al (2010) suggest that secondary education enrollment is more important for GDP per capita growth in developing than developed countries, while tertiary education is significant for both groups of countries, using the same techniques. Suri et al (2011) via OLS find a positive impact of enrollment rates on growth, while Phillips and Chen (2011) using multiple imputation techniques report a negative correlation between these variables. Furthermore, Hanushek and Woessmann (2011) employing added-variable techniques, show that if scores are ignored from growth regressions, schooling years are significantly related to growth, but when scores are included, schooling years become statistically insignificant.

The least common type of analyses use time series data, since education data with a long time-series dimension is relatively rare. Musila and Belassi (2004) applying OLS, report a positive effect of education expenditure on growth, whereas Ndiyo (2007), employing a vector autoregressive (VAR) technique, finds a negative correlation between these variables. On the contrary, Nketiah-Amponsah (2009) show that education expenditures have no significant impact on the rate of change of GDP. Furthermore, Dauda (2010), using OLS, finds a positive effect of total education expenditure on GDP growth. By estimating an Error Correction Model via the 'one step' procedure, Odit et al (2010) report a positive effect of schooling years on GDP per-worker growth, while Nurudeen and Usman (2010) via least squares reveal that expenditure on education has a negative effect on GDP growth. Finally, Lawal and Iyiola (2011) conclude that primary enrollment and total expenditure on education have a negative impact on growth, whereas capital, recurrent education expenditure, gross capital formation, post-primary and tertiary education enrollment affect growth positively using OLS.

3. ALTERNATIVE MEASURES OF EDUCATION AND ECONOMIC GROWTH

As it is evident from the previous section, measures of education and economic growth used in the empirical literature vary. Education is a broad term and as a result, empirical studies face difficulties with its measurement. The literature uses several proxies. Most proxies concern measures of formal education and include literacy rates, enrollment rates and years of schooling. Literacy rates are typically defined as the proportion of the population aged 15 and older who are able to read and write a simple statement on his/her everyday life (UNESCO, 1993). However, literacy rates are not objectively and consistently defined across countries and omit important components of human capital (Le et al., 2005).

Enrollment rates measure the number of students enrolled at a given level of education relative to the population that, according to legislation, should be attending school at that level. Enrollment rates measure the current investment in human capital that will be reflected in the future stock of human capital. Nevertheless, they are poor proxies for the present stock of human capital for many reasons. For instance, enrollment rates can be at best satisfactory proxies for human capital only in some countries. Judson (2002) argues that secondary enrollment rates will only be good indicators for human capital accumulation in countries where secondary education is expanding rapidly.

The deficiencies of literacy and enrollment rates as measures of human capital have motivated researchers to look for a more powerful human capital proxy, namely years of schooling of the workforce. Schooling years quantify the accumulated educational investment in the current workforce and assume that human capital embodied in workers is proportional to the years of schooling they have attained. With respect to literacy and enrollment rates, schooling years take into account the total amount of formal education acquired by the workforce, that is, schooling years proxy more accurately the existing stock of human capital in a country (Bassetti, 2007). In this context, some studies use the percentage of the working age population with primary, secondary and tertiary education. All these measures reflect the quantity of human capital. So, the above proxies do not give an indication of the skill level of the workforce.

Here comes the issue of human capital quality. The lack of human capital quality data in many studies considering the relationship between education and growth may be the biggest challenge in this area of research. The quantity of education is an inadequate measure of human capital differences, since school systems vary across countries in terms of resources, organization and duration. One solution in order to account for qualitative differences across education systems, is to focus on human capital quality measures, such as educational expenditure, student-teacher ratios and test scores. These indicators can be measured at different levels of education. However, using such quality measures as proxies of human capital, it is very difficult to get a measure that can be reliably extrapolated for the entire workforce. As a result, any possible measure of education has advantages and disadvantages, and they must be taken into account when the effect of education on economic growth is estimated.

Moreover, the output measure used varies across studies, being Gross Domestic Product (GDP), GDP per-capita or GDP per worker in real terms.[2] The respective output growth measures used as dependent variables are real GDP growth, real GDP per capita growth or real GDP per worker growth. From the previous discussion, we can argue that the coefficients estimating the relationship between education and economic growth may differ between studies partly due to differences in the type of the education and output variables used.

4. META-DATA SET AND STRATEGY

Following Stanley (2001), we proceed in two steps for conducting meta-regression analysis. First, we construct the meta-data set. In particular, we collect empirical studies examining the link between education and economic growth. Second, we define a meta-regression model. In this context, we examine particular independent meta-variables in order to distinguish between numerous criteria that appear important. Meta-regression analysis allows us to synthesize all empirical results in a common framework. The adopted expression for the meta-regression analysis is similar to the relation described by Stanley and Jarrell (1989).

At this point, we should note that the empirical studies on the relationship between education and income growth can be attributed to two theoretical approaches: the first is the micro literature based on the Mincer approach implying a positive relation between individual education and earnings (private returns), and the second is the macro literature which studies the relation between education and the capacity of a society to grow (social returns). We proceed by including only macro studies in our meta-sample which include the coefficient of the size effect of education on economic growth. Therefore, only studies providing regression results where economic growth is considered as the dependent variable and education as one explanatory variable are included in our meta-data set. We exclude from the analysis papers that focus on education as a private human capital investment estimating the rate of return to this investment (Harmon et al, 2003).[3] This process does not imply bias for our results, since our study examines the macroeconomic effects of education on economic growth.

Furthermore, the empirical literature that investigates the impact of education on growth includes estimates that have been reported in published academic journals as well as working papers, such as NBER or MPRA series. Many such works have been found in our search and, as a result, we included them in the meta-regression analysis. In particular, we have searched on the internet, the Econlit database, as well as the Google Scholar search engine, in order to find published articles in academic journals and working papers, concerning the education-economic growth nexus. The keywords used in this process were: human capital, education and economic growth and our last search was conducted on September 29, 2011.

In particular, we perform a meta-regression analysis using data from 56 empirical studies. As we include all reported estimates in each study, any potential dependence among estimates is best captured by using study identifiers. Given that most studies include plenty of estimations, we use all of them as independent regressions and as a result, we report a total of 979 observations. For comparison, Nelson and Kennedy (2009) in a survey of 140 meta-analyses conducted in environmental economics since 1989, report that an average meta-analysis employs 92 estimates (Irsova and Havranek, 2013). Therefore, our dataset is large relative to that of conventional economics meta-analyses.

Table 1 (Table 1 here) presents all studies employed in our meta-regression analysis and descriptive statistics of the estimated coefficient of education on economic growth. This table shows that there is great variation in findings across as well as within studies. Each study has a different mean value of the education coefficients and a different number of coefficients, which may be positive or negative. We employ meta-regression analysis, in order to explain the excess study-to-study variation found. Such an empirical research environment suggests using the following meta-regression model to integrate and explain the above mentioned diverse findings:

$$\beta_j = \beta_0 + \sum_{k=1}^{K} \alpha_k Z_{jk} + \beta_1 se_j + u_j \quad (j=1,2,...,56) \qquad (1)$$

where β_j is the reported estimate of the education coefficient of the j^{th} study, β_0 is the true value of the education coefficient, Z_{jk} are the moderator variables that influence the magnitude of the published results and explain variation in coefficients β_j, α_k are the meta-regression coefficients which reflect the effect of particular study characteristics, se_j is the standard error of the coefficient of the j^{th} study and u_j is the meta-regression disturbance term. We introduce se_j

because if there is publication selection, authors of small-sample studies search for larger estimates because such studies tend to have large standard errors. Large-sample studies typically find statistically significant estimates and can be published with smaller estimated effects. Therefore, the reported effect will be proportional to its standard error, ceteris paribus (Stanley et al., 2008).

In economics, though, empirical studies use different sample sizes and different econometric specifications and estimation procedures. Hence, the random estimation errors of the previous MRA model (u_j), are likely to be heteroscedastic.[4] Thus, the above equation is rarely estimated. Rather, its Weighted Least Squares (WLS) version, which divides this equation by se_j, becomes the obvious method of obtaining efficient estimates:

$$t_j = \beta_1 + \sum \gamma_i K_{ij} + \beta_0 \left(1/se_j\right) + \sum \alpha_k Z_{jk}/se_j + v_j \tag{2}$$

where t_j is the t-statistic which corresponds to the estimate β_j. Because publication selection is a complex phenomenon, we have replaced β_1 in (1) by $\beta_1 + \Sigma\gamma_i K_{ij}$ in (2), where K_{ij} are additional factors correlated with the publication process itself, e.g. socio-economic variables thought to affect publication selection (Doucouliagos and Stanley, 2009). That is, we control for heterogeneity in the Z variables, but not the K variables. Equation (2) can be used as a valid test for both the presence of publication selection bias (variables not divided by se_j) and genuine education effects on economic growth corrected for publication selection (variables divided by se_j) (Stanley 2005, 2008). We follow Efendic et al (2011) and use the Funnel Assymetry Test (FAT) to formally test for the presence of publication bias.[5]

We estimate our meta-regression model, in order to examine the extent to which the variables, with values defined for each study in our analysis, explain heterogeneity in the education effect on growth. Our meta-regression analysis focuses on the results of general-to-specific modelling, applied to the complete set of 979 estimates. That is, all *Z* and *K* variables were included in a general meta-regression model estimated, and then the statistically insignificant ones were removed, one at a time, to derive the specific model. In this framework, both genuine effect and publication bias are more complicated. Genuine effects (and/or large-sample biases) are now captured by the combination of all the *Z*-variables (divided by *se*), while the *K*-variables (not divided by *se*), along with the intercept, together represent publication selection (Doucouliagos and Stanley, 2009).

We introduce variables expected to have a systematic impact on the reported effect of education on economic growth. At the same time, it is necessary to limit the number of covariates relative to the number of studies in order to avoid false positive results (Thomson and Higgins, 2002). Specifically, we examine whether differences across studies can be attributed to differences in the measurement of education and economic growth. Among the most popular proxies for the quantity of education are literacy rates, school enrollment rates and educational attainment, measured in years of schooling of the working-age population. Also, three measures are used in order to account for qualitative differences across education systems, being student-teacher ratios, educational expenditures and international test scores. As a result, in order to examine the impact of alternative education proxies we use six dummy variables. The first three dummy variables (literacy, enrollment and schooling years) equal one, if the study uses the literacy rate, the school enrollment rate and years of schooling as proxies of the quantity of human capital respectively. The other three variables (student-teacher ratios, educational expenditure and scores), equal one, if the study uses student-teacher ratios, expenditure on education and international test scores as alternative measures of the quality of human capital. We omit the percentage of working-age population with primary, secondary or tertiary education as a proxy for the quantity of human capital, in order to avoid multicollinearity.

Furthermore, the output measure employed as dependent variable varies across studies. In order to study the effect of alternative economic growth measures on the reported findings, we include one dummy variable in our meta-regression model which equals one, if the study uses the real GDP growth rate as a proxy for economic growth. We omit real GDP per-capita growth as a proxy for economic growth due to multicollinearity.

We adopt additional moderator variables in order to examine whether particular characteristics of empirical approaches explain the variation in the reported findings. These variables were chosen on the basis of theoretical literature concerning the importance of each variable (Doucouliagos and Stanley, 2009, Adam, Kammas and Lagou, in press). In particular, we use the earliest and the latest year of the sample in each study to explore if the sample period influences the estimated education coefficient due to structural change. We also include dummy variables examining whether each study has been published in an academic journal or in the "best" 65 journals listed in Mamuneas et al (2010) and ESA (2008). In order to achieve comparable results, we include the same number of the "best" journals in the latter two cases. Moreover, we employ dummies reporting whether estimates are related to cross-sectional or panel data, with time series as the base, and whether the OLS method of estimation is employed, in order to control for differences in the type of data and methods of estimation respectively. In addition, we use dummy variables reflecting whether estimations include openness, a political measure, government spending and population growth as explanatory variables. We also use a dummy reflecting whether estimates rely on log specification, which is commonly used in empirical studies. Finally, we introduce the publication year of each study to investigate the existence of a time pattern in research output. All these are used as Z moderator variables that explain variation in the education coefficients. As a *K* variable correlated with the publication process itself, we use the sample size employed in each empirical work. This is because we expect that reviewers and editors tend to be suspicious and less favorable towards small-sample studies, reducing the chances for them to be published. All potential *Z* and *K* moderator variables employed in our meta-regression analysis are presented in Table 2 (Table 2 here).

5. ESTIMATION METHODOLOGY

Meta-regression analysis, or meta-regression, is an extension to standard meta-analysis that investigates the extent to which statistical heterogeneity between results of multiple studies can be related to one or more characteristics of the studies (Thompson and Higgins, 2002). It is very unlikely that all heterogeneity will be explained, so there will be "residual heterogeneity", therefore random effects rather than fixed effects meta-regression is appropriate. All algorithms for random-effects meta-regression first estimate the between-study variance and then estimate the coefficients by weighted least squares, using as weights the inverse sum of the standard error of the estimated effect in each study and the between-study variance. So, more accurate studies have more weight in the analysis. In our case, the between-study variance represents the excess variation in observed growth effects of education that is expected from the imprecision of results within each study.

Several methods have been proposed for the estimation of the between-study variance in meta-regressions. As suggested by Thompson and Sharp (1999), the unknown variance of the random-effect model can be computed by an iterative residual (restricted) maximum likelihood process (REML), the Empirical Bayes (EB) method (see also Morris, 1983), or a moment-estimator (MM). The main problem of likelihood methods is that they become computationally intensive and time consuming as the number of studies increases. The benchmark method for estimating the between-study variance is REML. It was developed in order to avoid the biased variance component estimates produced by ordinary maximum likelihood (ML) estimation, because ML estimates of variance components do not take into account the degrees of freedom used in estimating effect size in fixed effects. So, REML avoids downward biased estimates of the between-study variance, underestimated standard errors as well as anticonservative inference (Thompson and Sharp, 1999). The MM estimator, the only non-iterative method, has the advantages of speed and robustness. It does not require numerical maximization or iteration, is not time consuming and performs relatively well in comparison with likelihood methods with both simulated and real data sets. Results are expected to be similar to those obtained by likelihood methods when there is moderate to large heterogeneity. However, ML are often preferred to MM methods as the former have higher probability of being close to the quantities to be estimated (Mavridis and Salanti, 2012). From another point of view, the main advantage of the meta-analysis in a Bayesian framework is that external evidence or information from historical data can be easily incorporated in the model via informative priors. When the number of studies is large, the choice of prior distribution affects the results less, since data play the dominant role. However, when the number of studies is small, priors' selection is important. Both REML and EB estimators, being iterative methods, use the MM estimator as starting value.

Finally, since most studies in our sample report more than one regression, it is likely that observations (education coefficients) are correlated within studies. In light of that, we also estimate our model by OLS with heteroskedasticity cluster-robust standard errors, which allow for error term correlation within each cluster (study) [6], assuming only that they are not correlated across studies (Baum, 2006).[7] Thus, we relax the usual requirement that the observations are independent. We use this estimation method as a benchmark, because it is the simplest one and is used in many meta-regression works (e.g. Doucouliagos and Stanley, 2009, Effendic et al., 2011), although it is less appropriate for meta-regression analysis compared to the methods described previously. This is because, it does not account for the role of the between-study variance in the estimation of the coefficients in the meta-regression equation.

6. META-REGRESSION RESULTS

(a) Publication selection

Publication bias has been a primary concern for meta-analysts, as journals are more likely to publish studies reporting statistically significant results. Papers reporting insignificant results are either not submitted for publication or routinely rejected by the editors/referees (Bom and Ligthart, 2008). Thus, the authors treat statistically significant results more favorably, because they are more likely to be published. In light of these, we initially test whether there is publication bias in the education-growth literature.

The simplest method to detect publication selection is a visual examination of a funnel plot, which depicts the estimates of the coefficient in question on the horizontal axis and the inverse of their standard errors on the vertical axis. The expected shape is an inverted funnel, in the absence of publication selection, i.e. estimates should vary randomly and symmetrically around the true population effect. In figure 1 (Figure 1 here), we see that in our case, the funnel graph is asymmetric, as the plot is overweighed on the right side. Thus, we visually inspect the presence of publication selection bias towards positive values of the growth effect of education.

However, graphs are only subjective tests for examining publication bias. For this reason, we employ an objective statistical test for modelling publication selection, assuming that all α_k and γ_i are zero (there is no heterogeneity effect), that is the conventional t-test of the intercept of the equation:

$$t_j = \beta_1 + \beta_0 \left(1/se_j\right) + e_j \tag{3}$$

i.e., the Funnel Asymmetry Test or FAT (Egger et al, 1997, Stanley, 2005). If the literature is free of publication bias, the constant term should not be statistically significant (accept H_0: $\beta_1=0$). On the contrary, a non-zero constant term implies upward or downward bias on the effects estimated in the literature. The FAT test confirms the presence of publication bias (Table 3 here). The constant term is positive and statistically significant for all estimators. Therefore, we confirm the presence of "substantial" upward publication bias, since the estimate of β_1 is between 1 and 2 (Doucouliagos and Stanley, in press). This model can also be used to test for a genuine effect beyond publication selection. The coefficient on precision, β_0, can be considered an estimate of the empirical effect corrected for publication selection. Applying this precision-effect test (PET), cluster data analysis and MM imply that there is no evidence of a genuine education effect on growth. On the contrary, REML and EB results suggest a positive genuine education growth effect. However, even in these cases the impact is extremely small.

Table 4 (Table 4 here) presents the empirical results of our complete MRA model with a dummy for publications in academic journals, applying cluster data analysis, REML, MM and EB. Table 5 (Table 5 here) presents the empirical findings including a dummy for publications in journals listed in Mamuneas et al (2010), while Table 6 (Table 6 here) presents the empirical evidence of our meta-regression with a dummy for publications in journals listed in ESA (2008). In this way, we check the robustness of our findings to alternative quality measures of the publication outlets.

We proceed by estimating our meta-analysis regression separately with a dummy for publications in academic journals, journals listed in Mamuneas et al (2010) and journals included in ESA (2008), respectively, excluding 5% of the most extreme values of the effect of education on economic growth in Tables 7-9 (Tables 7-9 here). We do these robustness checks in order to examine the influence of extreme estimates on our findings.

We have evidence of substantial publication selection in our specific MRA model for the whole sample (Tables 4-6 here). Applying clustered data analysis, REML, MM and EB, the constant term is positive, large and statistically significant at all levels. However, the constant term itself is no longer a measure of the magnitude of the average publication bias. Rather, publication bias is the combination of the intercept and the *K* variable, i.e. sample size, which, however, is insignificant in all our estimations. Therefore, there is strong upward publication selection bias in the education-economic growth literature. This confirms the results obtained from the initial FAT-PET MRA, as well as visual examination of the funnel plot, although the magnitude of the bias is slightly smaller.

Excluding 5% of the extreme values of the effect of education on economic growth (Tables 7-9 here), our main results remain qualitatively and quantitatively very similar. Using all estimators, the constant term continues to be positive, large and statistically significant at all levels of significance. Moreover, publication bias is the combination of the intercept and the *K* variable (sample size), which is again insignificant in all estimations. Therefore, all findings imply the presence of substantial upward publication selection bias in the education-economic growth literature.

(b) Effects on human capital coefficients

(i) Whole sample estimations

In our specific meta-analysis regression of the whole sample with a dummy for publications in academic journals in Table 4 (Table 4 here), the overall fit of the regression is quite high for a meta-regression (R^2=0.19-0.78). Education effects on growth are the combination of several factors. When all Z-variables are zero[8], in the model with a dummy for publications in academic journals vs. working papers, education is predicted to have a contemporaneous negative and statistically significant effect on growth in all cases. Additionally, applying all techniques, specifications using education proxies based on enrollment rates increase the education effect on economic growth approximately by 0.004, whereas those using student-teacher ratios reduce it by around 0.002. The variation in reported estimates can be also explained by the inclusion of the earliest year of the sample and the type of data employed (cross-section and panel data), as well as openness and whether a particular study has been published in academic journals. The former three variables increase the education effect on growth approximately by 0.0001, 0.02 and 0.02 respectively, while the latter two reduce it by around 0.008 and 0.01. Moreover, all findings, apart from those obtained through MM, imply that the inclusion of log specification and the latest year of the sample as additional variables increase the growth impact of education by around 0.002 and 0.00007 respectively. In addition, only cluster data analysis results show that real GDP growth reduces this effect approximately by 0.007.

Similar results are obtained from the meta-analysis regression of the whole sample with a dummy for publications in journals listed in Mamuneas et al (2010) in Table 5 (Table 5 here) and ESA (2008) in Table 6 (Table 6 here). Differences across studies can be attributed to differences in the measurement of education, model specification, whether a particular study has been published in journals listed in Mamuneas et al (2010) or ESA (2008) and the type of data employed.

However, in these regressions (Tables 5 and 6 here), output data, as well as education data based on student-teacher-ratios, can not explain the variation in reported estimates. In addition, the sample period, i.e. the earliest and the latest year of the sample, plays no role. On the contrary, the heterogeneity of the empirical findings can be attributed to the use of test scores and political measures which increases the education effect on growth by 0.003 and 0.004 respectively. The heterogeneity is also due to the inclusion of OLS estimation and population growth, which reduce the education impact on growth by 0.003 and 0.001.

(ii) Estimations excluding the most extreme values of the effect of education on growth

If we exclude 5% of the most extreme values of the effect of education on economic growth, our main results remain qualitatively and quantitatively intact for all regressions (see Tables 7-9). (Tables 7-9 here). In particular, all estimators suggest a significant impact of education on economic growth. In all cases, differences in the measurement of education, model specification, and type of data employed give rise to different findings concerning the effect of education on growth. Moreover, whether a particular study has been published in academic journals, journals listed in Mamuneas et al (2010) and ESA (2008), as well as the inclusion of openness as explanatory variables account for the variation of the empirical evidence. Furthermore, for journals listed in Mamuneas et al and ESA, the heterogeneity of the results can be also explained by the use of a political measure, as well as OLS and population growth as additional variables. Finally, only in the case of academic journals, the sample period and the output data employed in each study appear to affect the reported estimates.

7. CONCLUSIONS

In this paper, we have seen that a large body of macroeconomic literature has focused on the relationship between education and economic growth. Empirical findings on this link are controversial. Their interpretation must take into account several conceptual and methodological problems. Most importantly, educational attainment, commonly used in empirical studies, is a crude measure of human capital, since the education quality varies widely across countries. Also, low data quality for educational attainment as well as important econometric issues, such as omitted variables bias, parameter heterogeneity, reverse causality and non-linearity, are factors responsible for the non-robustness of the results. In light of these, we make an attempt to evaluate the empirical literature on the effect of education on growth and explain the wide variation in reported estimates.

Specifically, we analyze the findings of 56 empirical studies and apply meta-regression analysis using four estimators, correcting for possible publication selection bias in the relevant literature. We investigate the impact of several factors on the variation of the reported estimates of the growth impact of education. Our MRA analysis produces interesting results, which are robust to different estimators, the inclusion of various types of research outlets and the presence of outliers in our data set.

First, we confirm the presence of substantial upward publication selection bias in the education-economic growth literature, while we find no evidence of a large amount of unexplained heterogeneity. Second, all methods indicate a significant genuine education effect on growth after correction for publication selection. Third, differences across studies can be partially attributed to differences in terms of their characteristics. Specifically, the inclusion of education enrollment, test scores, political measures, the use of cross-section or panel data instead of time series and log specification, tend to make the impact of education on growth corrected for publication bias less negative. On the contrary, the use of student-teacher ratio, OLS estimation, openness, population growth and publication in a high-quality journal tend to make the growth impact of education more negative. However, only in the case of research published in academic journals vs. working papers, alternative economic growth measures are found to explain the heterogeneity of the research findings.

Thus, it seems safe to conclude that the education-economic growth empirical research, exhibits substantial publication selection toward positive growth effects of education, while the economic growth impact of education after taking into account publication bias depends critically on the specific features of the study. These findings do not necessarily imply that the positive impact of education on growth postulated by theory does not exist. It may well be the case that the problems characterizing empirical research on this question are so severe that they make it impossible to uncover this effect. In any case, our paper provides important information for future empirical studies evaluating the role of education in the process of economic growth.

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ENDNOTES

1. The ranking we use by Mamuneas et al (2010) is an update of the well-known ranking of economics journals by Kalaitzidakis, Mamuneas and Stengos (2003). In contrast with their earlier ranking, in the more recent work they use a rolling window of years for 2003-2008, i.e. for each year they count the number of article citations published in the previous ten years. This allows them to attain a smoother longer view of the evolution of rankings in the examined period and thus avoid the possible randomness at any specific year. The ranking by ESA (2008) is the latest ranking conducted by the Economic Society of Australia and it is used for the evaluation of research output in Australia.

2. We do not consider studies that examine other measures of growth, e.g. TFP growth.

3. In several studies the authors do not report t-statistics. These studies were either excluded from the analysis or, if they provide standard errors or p-values, the missing t-statistics were retrieved.

4. We employed a Cook-Weisberg test in order to test the residuals for heteroscedasticity. In our case, we obtain a significant test statistic implying heteroscedasticity in the residual series in regression (1) in the text in our case.

5. Monte Carlo simulations have shown FAT to perform reasonably well even when publication selection is severe (see Stanley, 2008, p.106).

6. When we build our regression model, we assume that the dependent variable is a linear combination of the independent variables and assume that this function is the correct one to use. Moreover, on the right-hand side of the equation, we assume that we have included all the relevant variables that we should use in the model. So, we employ a link test for cluster data analysis, in order to detect a specification error of the model and as a result, the model appeared correctly specified (see Adam, Kammas and Lagou, in press, p. 8).

7. Moreover, with regard to cluster data analysis results, we perform a regression specification error test for omitted variables, namely the Ramsey Reset test, which does not reject the null

hypothesis (Ho: the model has no omitted variables), indicating correct specification of our model (see Efendic et al, 2011, p.593).

8. Testing H0: $\beta 0 = 0$ may provide a valid and powerful test for genuine effect beyond publication selection bias. However, the validity of this test needs to be qualified. Simulations show that PET can be relied upon if the heterogeneity (or the magnitude of misspecification biases) is not too large. If there is large unexplained heterogeneity and a high incidence of publication selection, the above test can suffer from type I error inflation. The failure to reject H_0: $\sigma^2_v \leq 2$ serves as an effective means to limit these potential type I errors (see Stanley 2008), where σ^2_v is the error variance in the MRA model. Regarding cluster data analysis results, we have no evidence of a large amount of unexplained heterogeneity (accept H_0: $\sigma^2_v \leq 2$) at any significance level. As a result, we can rule out a type I error as a likely cause of this significant PET result (see Stanley et al, 2008, p. 282). Thereby, we can rely upon PET to determine genuine effect.

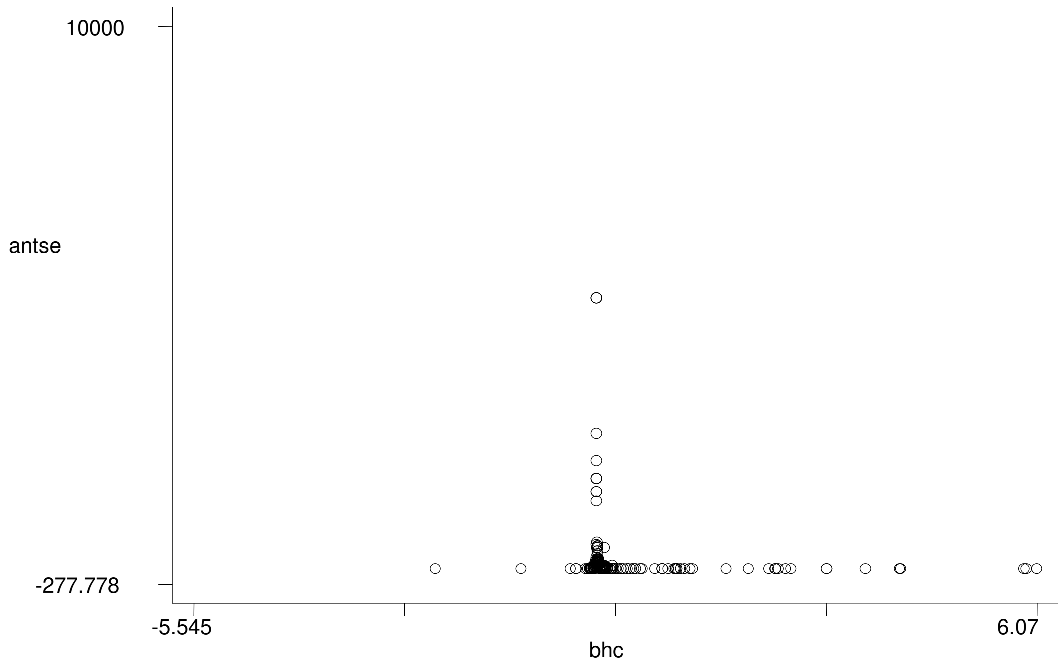

Figure 1: Funnel Graph.

Note: The variables bhc and antse represent the education coefficient and the inverse of the standard error (antse=1/standerror) respectively.

Table 1: Summary statistics of the studies included in meta-regression analysis

Authors, publication year	Number of coefficients	Minimum	Maximum	Median	Mean	Standard deviation
Romer, 1989	3	0.0062	0.0386	0.0155	0.016683	0.0201
Azariadis-Drazen, 1990	3	0.0025	0.0122	0.0103	0.00514	0.008333
Barro, 1991	48	-0.0171	0.0385	0.02365	0.01288	0.019713
Murphy et al, 1991	10	-0.078	0.125	0.001	0.061176	0.0059
Levine-Renelt, 1992	10	0.63	3.71	1.5	1.128315	1.915
Mankiw et al, 1992	3	0.223	0.271	0.233	0.025325	0.242333
Benhabib-Spiegel, 1994	23	-0.092	0.167	-0.028	0.075593	-0.00515
Durlauf-Johnson, 1995	7	-0.114	0.469	0.209	0.20288	0.174857
Lee-Lee, 1995	11	-0.0042	0.0128	0.0016	0.004034	0.001946
Barro, 1996	9	-0.0032	0.11	0.0116	0.033761	0.020989
Gemmell, 1996	30	-2.21	6.07	1.11	2.016531	1.619
Collins-Bosworth, 1996	7	0.04	0.25	0.15	0.075907	0.145714
Bloom et al, 1998	2	0.087	0.37	0.2285	0.200111	0.2285
Temple, 1999	4	0.063	0.165	0.109	0.041773	0.1115
Bils-Klenow, 2000	2	0.213	0.3	0.2565	0.061518	0.2565
Hanushek-Kimko, 2000	24	0.034	0.548	0.105	0.124418	0.136833
Ranis et al, 2001	2	0.03	0.03	0.03	0	0.03
Bassanini- Scarpetta, 2001	16	0.41	1.76	0.9	0.326624	0.898125
Kalaitzidakis et al, 2001	64	-2.19	0.288	0.007	0.296553	-0.03719
Prichett, 2001	7	-0.12	0.058	-0.049	0.062909	-0.04486
Krueger-Lindahl, 2001	58	-0.072	0.614	0.006	0.092175	0.031791
Barro, 2001	22	-0.025	0.129	0.0032	0.043526	0.030509
Appiah-McMahon, 2002	2	0.0003	0.0016	0.00095	0.000919	0.00095
Knowles et al, 2002	4	0.076	0.23	0.149	0.084998	0.151
Papageorgiou, 2003	48	-0.4087	0.3415	0.0405	0.124357	0.058865

Bosworth-Collins, 2003	10	0.07	1.55	0.33	0.481762	0.465
Chakraborty, 2004	5	0.27	4.45	1.43	1.64963	2.124
Barro-Sala-i-Martin, 2004	14	-0.057	0.121	0.00235	0.036619	0.007114
Musila-Belassi, 2004	1	0.036	0.036	0.036	.	0.036
Gyimah-Brempong et al, 2006	10	-0.0299	0.1281	0.05915	0.051956	0.05392
Keller, 2006	63	-5.545	4.675	-0.009	1.630914	-0.20657
Siddiqui, 2006	18	-0.78	0.4475	0.063	0.299319	-0.00202
Bose et al, 2007	11	-0.016	1.582	-0.012	0.502662	0.193182
Cohen-Soto, 2007	25	-0.049	0.123	0.017	0.047184	0.029068
Ndiyo, 2007	1	-0.327	-0.327	-0.327	.	-0.327
Hanushek et al, 2007	10	0.0078	0.459	0.0855	0.159945	0.15661
Sterlacchini, 2008	7	0.052	0.394	0.321	0.12977	0.266429
Costantini-Monni, 20008	6	-2.537	-1.568	-1.9605	0.344923	-2.021
Baldacci et al, 2008	10	-0.011	0.135	0.0875	0.053193	0.0718
Hanushek-Woessmann, 2008	20	-0.031	2.286	0.2605	0.850137	0.76135
Bhattacharyya, 2009	30	-0.0007	0.01	0.006	0.002014	0.005477
Nketiah-Amponsah, 2009	1	-0.3	-0.3	-0.3	.	-0.3
Seetanah, 2009	2	0.01	0.08	0.045	0.049498	0.045
Sandar-Macdonald, 2009	23	-0.001	0.019	0.0007	0.004193	0.001952
Chen-Gupta, 2009	12	-0.007	0.1429	0.01575	0.045707	0.031883
Lee-Kim, 2009	20	0.001	0.033	0.013	0.008688	0.013
Lee, 2010	6	0.0006	0.0032	0.00115	0.001132	0.001583
Dauda, 2010	1	1.4155	1.4155	1.4155	.	1.4155
Benos-Karagiannis, 2010	132	-0.086	0.783	0.001	0.113151	0.043174
Odit et al, 2010	3	0.0985	1.6547	1.3378	0.8224	1.030333
Tsai et al, 2010	24	-0.0029	0.0969	0.0024	0.032294	0.022592
Nurudeen-Usman, 2010	1	-0.0667	-0.0667	-0.0667	.	-0.0667
Suri et al, 2011	2	0.0183	0.0282	0.02325	0.007	0.02325
Phillips-Chen, 2011	16	-4.4663	3.5154	0.3519	1.924622	0.175419
Lawal-Iyiola, 2011	6	-2.643	1.984	0.4365	1.799473	-0.10317
Hanushek-Woessmann, 2011	70	0.012	2.35	0.161	0.842255	0.814714
Total	979	-5.545	6.07	0.0183	0.830403	0.181329

Table 2: K and Z variables for Meta-Regression Analysis (MRA)

Variables [a]	Description of the variable
t-statistic	the t-statistic of the coefficient of interest of the study
K-variables [b]	
sample size	the sample size used in the study
Z-variables [c]	
antse=1/standerror	1 / the standard error of the coefficient of interest of the study
literacy	=1, if the study uses the literacy rate as a proxy for education (quantity)
enrollment	=1, if the study uses the school-enrollment rate as a proxy for education (quantity)
schooling years	=1, if the study uses years of schooling as a proxy for education (quantity)
student-teacher ratios	=1, if the study uses the student-teacher ratio as a proxy for education (quality)
educational expenditure	=1, if the study uses educational expenditure as a proxy for education (quality)
scores	=1, if the study uses international test scores as a proxy for education (quality)
real GDP growth	=1, if the study uses real GDP growth as a proxy for economic growth
earliest year	the earliest year of the sample in the study
latest year	the latest year of the sample in the study

journal	=1, if the study has been published in an academic journal
Mamuneas et al	=1, if the study has been published in a journal listed in Mamuneas et al (2010)
ESA	=1, if the study has been published in a journal listed in ESA (Economic Society of Australia)
cross	=1, if estimate relates to cross-sectional data, with time series as the base
panel	=1, if estimate relates to panel data, with time series as the base
ols	=1, if the study employs the OLS method of estimation
openness	=1, if the study uses openness of the economies as an explanatory variable
political	=1, if the study uses a political measure as an explanatory variable
government spending	=1, if the study uses government spending as an explanatory variable
population growth	=1, if the study uses population growth as an explanatory variable
log specification	=1, if the study employs a log specification
publication year	the year the study was published

[a] All variables are included as Z and K variables in a general-to-specific modelling approach.
[b] K variables may affect the likelihood of being selected for publication.
[c] Z variables may affect the magnitude of the education coefficient.

Table 3: Funnel Asymmetry Test

Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse	0.000610	0.000606	0.000609	0.000606
	(1.34)	(5.26)***	(1.51)	(5.29)***
constant	1.694401	1.707225	1.698321	1.707282
	(6.49)***	(15.59)***	(4.47)***	(15.69)***
R-squared	0.0282	0.0267	0.068	0.027
Ramsey RESET test	F(3,974)=11.26 Prob>F=0.0000 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the FAT results with cluster-robust standard errors.
[b] The Ramsey reset test rejects the null at all levels of statistical significance, indicating an incorrect specification of the model.
[c] REML presents the FAT results with restricted maximum likelihood.
[d] MM presents the FAT results with the moment estimator.
[e] EB presents the FAT results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 4: Meta-analysis regression with a dummy for publications in academic journals

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.327***	-0.328***	-0.240***	-0.328***
	(-7.043)	(-5.890)	(-2.993)	(-5.928)
sample size				
literacy/se				
enrollment/se	0.00475***	0.00477***	0.00323**	0.00477***
	(4.385)	(4.975)	(2.225)	(5.006)
schooling years/se				
student-teacher ratios/se	-0.00152***	-0.00150***	-0.00243***	-0.00150***
	(-5.636)	(-3.057)	(-3.261)	(-3.077)
educational expenditure/se				

scores/se				
real GDP growth/se	-0.00655***			
	(-3.118)			
earliest year/se	9.30e-05***	9.23e-05***	0.000120***	9.23e-05***
	(6.310)	(4.021)	(2.974)	(4.047)
latest year/se	6.82e-05***	6.93e-05***		6.93e-05***
	(3.739)	(2.804)		(2.821)
journal/se	-0.0104***	-0.0104***	-0.00943***	-0.0104***
	(-2.782)	(-6.051)	(-3.064)	(-6.090)
cross/se	0.0198***	0.0199***	0.0153***	0.0199***
	(4.283)	(7.755)	(3.810)	(7.804)
panel/se	0.0178***	0.0179***	0.0152***	0.0179***
	(4.184)	(7.713)	(4.001)	(7.762)
ols/se				
openness/se	-0.00802***	-0.00804***	-0.00667***	-0.00804***
	(-7.098)	(-8.139)	(-4.261)	(-8.191)
political/se				
government spending/se				
population growth/se				
log specification/se	0.00220**	0.00227***		0.00227***
	(2.399)	(3.115)		(3.134)
publication year/se				
constant	1.566***	1.569***	1.560***	1.569***
	(6.400)	(15.09)	(8.185)	(15.19)
R-squared	0.1980	0.1891	0.7778	0.1901
Ramsey RESET test	F(3, 964) = 2.31			
	Prob > F = 0.0748 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.
[b] The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 5: Meta-analysis regression with a dummy for publications in journals listed in Mamuneas et al

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.00984***	-0.00983***	-0.00891***	-0.00983***
	(-4.611)	(-6.976)	(-3.404)	(-7.020)
sample size				
literacy/se				

enrollment/se	0.00521***	0.00520***	0.00415**	0.00520***
	(4.120)	(5.485)	(2.357)	(5.520)
schooling years/se				
student-teacher ratios/se				
educational expenditure/se				
scores/se	0.00321**	0.00322***		0.00322***
	(2.594)	(3.144)		(3.163)
real GDP growth/se				
earliest year/se				
latest year/se				
Mamuneas et al/se	-0.00372***	-0.00373***		-0.00373***
	(-3.049)	(-4.218)		(-4.245)
cross/se	0.0117***	0.0116***	0.00939***	0.0116***
	(5.082)	(8.117)	(3.599)	(8.168)
panel/se	0.00689***	0.00690***	0.00380**	0.00690***
	(5.273)	(6.471)	(2.552)	(6.511)
ols/se	-0.00339***	-0.00339***	-0.00519***	-0.00339***
	(-2.808)	(-3.924)	(-4.097)	(-3.949)
openness/se	-0.00708***	-0.00707***	-0.00375***	-0.00707***
	(-5.372)	(-6.914)	(-2.809)	(-6.958)
political/se	0.00359***	0.00359***	0.00308***	0.00359***
	(4.122)	(5.831)	(2.714)	(5.868)
government spending/se				
population growth/se	-0.00124***	-0.00123***		-0.00123***
	(-6.744)	(-3.476)		(-3.498)
log specification/se	0.00620***	0.00619***	0.00507***	0.00619***
	(5.175)	(7.680)	(3.620)	(7.728)
publication year/se				
constant	1.610***	1.623***	1.634***	1.623***
	(6.532)	(15.66)	(8.247)	(15.76)
R-squared	0.1919	0.1830	0.7587	0.1839
Ramsey RESET test	F(3, 964) = 2.32 Prob > F = 0.0743 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.
[b] The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 6: Meta-analysis regression with a dummy for publications in academic journals listed in ESA

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.0101***	-0.0101***	-0.00891***	-0.00762***
	(-4.756)	(-7.105)	(-3.404)	(-5.349)
sample size				
literacy/se				
enrollment/se	0.00531***	0.00530***	0.00415**	0.00549***
	(4.222)	(5.589)	(2.357)	(5.778)
schooling years/se				
student-teacher ratios/se				-0.00299***
				(-2.847)
educational expenditure/se				
scores/se	0.00334***	0.00333***		
	(2.673)	(3.303)		
real GDP growth/se				
earliest year/se				
latest year/se				
ESA/se	-0.00392***	-0.00392***		-0.00144**
	(-3.199)	(-4.493)		(-2.253)
cross/se	0.0119***	0.0119***	0.00939***	0.00954***
	(5.259)	(8.252)	(3.599)	(6.554)
panel/se	0.00708***	0.00708***	0.00380**	0.00479***
	(5.393)	(6.666)	(2.552)	(5.065)
ols/se	-0.00333***	-0.00333***	-0.00519***	-0.00292***
	(-2.799)	(-3.908)	(-4.097)	(-2.984)
openness/se	-0.00728***	-0.00727***	-0.00375***	-0.00507***
	(-5.489)	(-7.122)	(-2.809)	(-5.649)
political/se	0.00367***	0.00368***	0.00308***	0.00361***
	(4.202)	(5.951)	(2.714)	(5.857)
government spending/se				
population growth/se	-0.00127***	-0.00126***		-0.00128***
	(-6.987)	(-3.562)		(-3.641)
log specification/se	0.00635***	0.00634***	0.00507***	0.00381***
	(5.342)	(7.820)	(3.620)	(4.197)
publication year/se				
constant	1.603***	1.616***	1.634***	1.588***
	(6.559)	(15.62)	(8.247)	(15.36)
R-squared	0.1938	0.1850	0.7587	0.1834
Ramsey RESET test	F(3, 964) = 2.23 Prob > F = 0.0834 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).

[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.

[b] The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 7: Meta-analysis regression with a dummy for publications in academic journals, excluding 5% of extreme values

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.325***	-0.325***	-0.240***	-0.325***
	(-7.085)	(-5.782)	(-2.997)	(-5.809)
sample size				
literacy/se				
enrollment/se	0.00472***	0.00475***	0.00325**	0.00475***
	(4.385)	(4.891)	(2.233)	(4.914)
schooling years/se				
student-teacher ratios/se	-0.00156***	-0.00154***	-0.00245***	-0.00154***
	(-5.902)	(-3.097)	(-3.274)	(-3.112)
educational expenditure/se				
scores/se				
real GDP growth/se	-0.00611***			
	(-2.956)			
earliest year/se	9.40e-05***	9.33e-05***	0.000120***	9.33e-05***
	(6.545)	(4.029)	(2.978)	(4.048)
latest year/se	6.58e-05***	6.69e-05***		6.69e-05***
	(3.645)	(2.677)		(2.689)
journal/se	-0.0109***	-0.0109***	-0.0100***	-0.0109***
	(-2.855)	(-6.078)	(-3.149)	(-6.106)
cross/se	0.0202***	0.0203***	0.0159***	0.0203***
	(4.407)	(7.781)	(3.892)	(7.818)
panel/se	0.0182***	0.0182***	0.0158***	0.0182***
	(4.274)	(7.721)	(4.078)	(7.757)
ols/se				
openness/se	-0.00801***	-0.00803***	-0.00670***	-0.00803***
	(-7.159)	(-8.035)	(-4.269)	(-8.073)
political/se				
government spending/se				
population growth/se				
log specification/se	0.00221**	0.00228***		0.00228***
	(2.463)	(3.085)		(3.100)
publication year/se				

constant	1.495***	1.497***	1.489***	1.497***
	(6.161)	(13.88)	(7.591)	(13.95)
R-squared	0.2060	0.1971	0.7777	0.1979
Ramsey RESET test	F(3, 914) = 2.07 Prob > F = 0.1020 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.
[b] The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 8: Meta-analysis regression with a dummy for publications in journals listed in Mamuneas et al, excluding 5% of extreme values

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.00990***	-0.00989***	-0.00898***	-0.00989***
	(-4.545)	(-6.922)	(-3.417)	(-6.954)
sample size				
literacy/se				
enrollment/se	0.00526***	0.00525***	0.00419**	0.00525***
	(4.114)	(5.480)	(2.370)	(5.506)
schooling years/se				
student-teacher ratios/se				
educational expenditure/se				
scores/se	0.00325**	0.00325***		0.00325***
	(2.568)	(3.141)		(3.156)
real GDP growth/se				
earliest year/se				
latest year/se				
Mamuneas et al/se	-0.00376***	-0.00376***		-0.00376***
	(-3.015)	(-4.193)		(-4.213)
cross/se	0.0118***	0.0117***	0.00949***	0.0117***
	(5.037)	(8.085)	(3.620)	(8.123)
panel/se	0.00694***	0.00694***	0.00380**	0.00694***
	(5.175)	(6.396)	(2.536)	(6.426)
ols/se	-0.00337***	-0.00336***	-0.00520***	-0.00336***
	(-2.714)	(-3.821)	(-4.077)	(-3.838)
openness/se	-0.00717***	-0.00716***	-0.00378***	-0.00716***
	(-5.295)	(-6.860)	(-2.808)	(-6.891)
political/se	0.00357***	0.00357***	0.00309***	0.00357***

	(4.008)	(5.717)	(2.698)	(5.743)
government spending/se				
population growth/se	-0.00126***	-0.00126***		-0.00126***
	(-6.957)	(-3.516)		(-3.533)
log specification/se	0.00628***	0.00627***	0.00515***	0.00627***
	(5.140)	(7.676)	(3.663)	(7.712)
publication year/se				
constant	1.540***	1.552***	1.569***	1.552***
	(6.267)	(14.43)	(7.684)	(14.50)
R-squared	0.1976	0.1898	0.7586	0.1905
Ramsey RESET test	F(3,914) = 1.93 Prob > F= 0.1230 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.
[b] The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 9: Meta-analysis regression with a dummy for publications in journals listed in ESA, excluding 5% of extreme values

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.0101***	-0.0101***	-0.00898***	-0.0101***
	(-4.693)	(-7.054)	(-3.417)	(-7.087)
sample size				
literacy/se				
enrollment/se	0.00537***	0.00536***	0.00419**	0.00536***
	(4.218)	(5.586)	(2.370)	(5.612)
schooling years/se				
student-teacher ratios/se				
educational expenditure/se				
scores/se	0.00338**	0.00338***		0.00338***
	(2.647)	(3.308)		(3.324)
real GDP growth/se				
earliest year/se				
latest year/se				
ESA/se	-0.00397***	-0.00397***		-0.00397***
	(-3.161)	(-4.478)		(-4.499)
cross/se	0.0120***	0.0120***	0.00949***	0.0120***
	(5.218)	(8.224)	(3.620)	(8.262)

panel/se	0.00714***	0.00714***	0.00380**	0.00714***
	(5.290)	(6.599)	(2.536)	(6.630)
ols/se	-0.00330***	-0.00329***	-0.00520***	-0.00329***
	(-2.695)	(-3.798)	(-4.077)	(-3.815)
openness/se	-0.00738***	-0.00737***	-0.00378***	-0.00737***
	(-5.409)	(-7.076)	(-2.808)	(-7.109)
political/se	0.00366***	0.00366***	0.00309***	0.00366***
	(4.090)	(5.838)	(2.698)	(5.865)
government spending/se				
population growth/se	-0.00129***	-0.00129***		-0.00129***
	(-7.166)	(-3.605)		(-3.622)
log specification/se	0.00643***	0.00642***	0.00515***	0.00642***
	(5.311)	(7.821)	(3.663)	(7.857)
publication year/se				
constant	1.533***	1.545***	1.569***	1.545***
	(6.291)	(14.39)	(7.684)	(14.45)
R-squared	0.2014	0.1919	0.7586	0.1927
Ramsey RESET test	F(3, 914) =1.87 Prob >F=0.1328 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] Cluster data analysis presents the MRA results with cluster-robust standard errors.
[b] The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.
[c] REML presents the MRA results with restricted maximum likelihood.
[d] MM presents the MRA results with the moment estimator.
[e] EB presents the MRA results with the empirical Bayes iterative procedure.
*, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.