A Meta-Analysis Of The Impact Of Education On Migration

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Abstract**—** *This paper represents a clear departure from the migration literature and a first attempt in applying a meta-analysis on the impact of education on migration behaviour. A three-part meta-analysis is applied on twenty-two rigorously selected studies examining education as one of the determinants of migration. The first part, the standard meta-analysis, finds that most of the effect sizes or the impact of the education variable to be positive, i.e. indicating that the more educated tend towards migrating. The summary impact of the education coefficient estimate is found to have a magnitude of approximately +0.300. The second part of the meta-analysis checks for publication bias; formal tests suggest no evidence of such bias in our meta-analysis. In the final part, a meta-regression is used to account for the source of heterogeneity in the coefficient estimates between studies, in which six of the study characteristics are found significant.*

Keywords- skilled migration; education; meta-analysis

I. Introduction

Education has often been singled out as the predominant determinant of migration. Education is almost always included as one of the regressors when explaining what determines migration, regardless if the issue is about skilled or the more general type of migration such as regional or rural-urban migration. Although a relatively large proportion of studies conclude that education has a significant and positive impact on migration, there appears to be no consensus in the literature on the magnitude (i.e. size of the coefficient estimate) and the direction (i.e. coefficient sign) of the impact. Some studies even find education to be statistically insignificant in determining migration.

Until recently, studies on the determinants of migration typically review the literature narratively and manipulate arguments subjectively to suit the stance of the studies. A meta-analysis is a quantitative literature review, where the literature is reviewed in a methodologically rigorous way with formal hypothesis tests and statistics to support the review. The objective of a meta-analysis is not to discredit certain studies (e.g. studies with unconventional negative coefficient of the education variable), but rather to integrate and synthesize the many often-contradicting findings and conclusions from the mushrooming literature.

Meta-analysis has its roots in the field of educational research, in which Glass [1, 2] is credited as the pioneer of this analytical approach. Meta-analysis is used in this field to assess, among others, the impact of teachers' qualifications on students' performance, and the types of learning intervention on examination scores. The meta-analysis approach gradually permeates into other fields such as psychology, biomedical science, pharmacology, ecology, criminology, and business. The breakthrough of meta-analysis into the field of economics is made through the seminal article in [3]. They went on to produce the first application of meta-analysis within economics in their study on the union-nonunion wage gap [4]. Following this, meta-analysis has been adopted in economic subfields such as education, labour, transportation, urban, and recreational economics.

In migration economics, meta-analysis has been applied mainly on the impact of migration – its impact on wages [5, 6], on employment [7], on income [8], and on international trade [9]. This paper looks at the other side of the coin, i.e. what determines migration. More specifically, this paper looks at how education impacts migration (both general and skilled migration). In the literature of migration economics, education plays a crucial role on migration behaviour; the better-educated appear to be more mobile than their less-educated counterparts.

There are, however, a number of studies that suggest otherwise, as revealed by the negative coefficient sign of the education variable [10, 11, 12, 13]. Such inconsistencies in individual studies may be due to either (i) real differences in how the education variable can impact migration, or (ii) differences in the characteristics of the migration studies. To date, there are yet to be any meta-analyses examining this issue – a gap this study is filling.

II. Methodology

A. *Methodology Set-up*

The primary objective of a meta-analysis is to synthesize the often individually inconclusive and seemingly irreconcilable results of a large number of studies, to come up with a summary effect size, i.e. the average coefficient estimate of the education variable in the context of this study. Its ability to synthesize individually disparate studies can yield more rigorously sound statistical evidence than the relatively less-convincing and often subjective narrative literature review. A meta-analysis starts by defining a dependent and an explanatory variable of interest. Here, the dependent variable is the migration behaviour (i.e. decision or intention), and the explanatory variable is the level or years of education obtained. A list of inclusion/exclusion criteria is then drawn up. Studies that meet the criteria will be included in the meta-analysis. These criteria are necessary so that the eventual dataset contains studies with a manageable degree of heterogeneity, and therefore facilitates comparison. Table 1 lists those criteria. Based on the above criteria, relevant literature on migration are scoured via electronic economic databases. When combing through these databases, the following keywords are used: brain drain, migration intention/decision/behaviour, skilled migration, and mobility propensity. For databases providing only abstract and bibliographical citations, every feasible attempt has been made to obtain the full text by searching in another database, or contacting the relevant authors. As suggested by [9], after the databases have been searched through, a last search via Google Scholar and Google is used to round up unpublished or 'fugitive' articles [14]. For every study selected to be included in the meta-analysis, its references section is also checked for relevant studies. At the end of the search, a total of 22 studies that fulfil the inclusion/exclusion criteria are selected. To construct the meta-analysis database, I first extract the coefficients of the education variable and their corresponding standard errors from the selected studies. For studies with multiple model specifications, the coefficient and standard error from the base model is extracted. These coefficients are the impact of education on migration behaviour. Along with these two statistics, I also compile and code other characteristics from each of the selected studies. The 'Meta-regression' section explains further.

TABLE I. INCLUSION/EXCLUSION CRITERIA

Features	Inclusion/exclusion criteria
	Include studies if
Dependent/outcome variable	Actual migration decision/behaviour; intention/willingness to migrate/move (all in terms of probabilities)
Explanatory variable of interest	Years of education; level of education
Migration type	International; rural-urban; non-return; skilled; non-skilled
Geographical context	Cross national border; regional; within national border (e.g. rural-to-urban)
Language	Study published in English
Data level	Micro-level; individual-level
Data type	Cross-sectional; panel
Sample of respondents	Survey; a percentage from census
Types of respondent	Working adults; students
Model specification	Discrete choice models
Publication type	Journal article; working paper; book; unpublished paper
	Exclude studies if
Dependent/outcome variable	Migration rates (i.e. ratio of migrants to total population); return migration
Explanatory variable of interest	No education variable
Study type	Theoretical/Conceptual/Descriptive papers with no empirical elements
Effect size	Not in the form of discrete choice model coefficient estimates
Statistics	No standard errors/t-statistics/coefficient estimates of the explanatory variable of interest (the education variable in this case), sample size

III. FINDINGS & DISCUSSIONS

A. *Meta-analysis*

Pane A in Table 2 shows the effect size of each study, i.e. the coefficient estimate of the education variable. As these coefficient estimates are obtained from discrete choice models, their magnitudes are not directly interpretable. The meta-analysis obtains a summary effect of +0.300, i.e. the average coefficient estimate of the impact of education on migration behaviour. Pane A can also be read along with the forest plot shown in Figure 1. The squares in a forest plot represent the effect sizes while the horizontal lines represent the confidence intervals of the effects. A larger sample size gives a smaller The area of the squares reflects the weight that a particular study [15]. Studies with better precision are given more weight, which is a function of sample size. The location of the squares indicates the direction and the magnitude of the effect [16]. It is obvious from Figure 1 that most of the effect sizes border on the positive pane, indicating that the more educated tend towards migrating.

Pane B shows how the impact of education shifts over time, since the studies are sorted chronologically from 1993 to 2011. Pane B can be read along with Figure 2. The effect size displayed in each row is the summary effect based on all the studies up to and including that row. There appears to be three clusters of summary effects shown in Figure 2, with the impact of education stabilizing starting mid-2000s. This indicates that in recent years, the impact of education has been consistently at a magnitude of approximately 0.300 (which is translated to its corresponding marginal change in the probability to migrate, depending on the discrete choice model used).

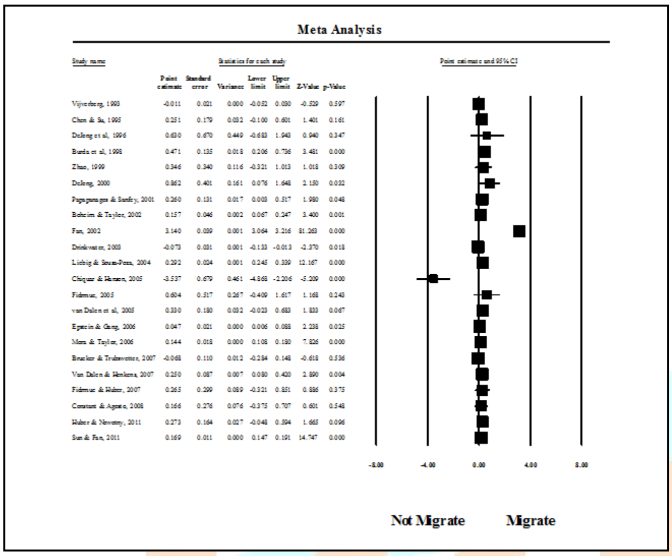

Figure 1. *Forest plot*

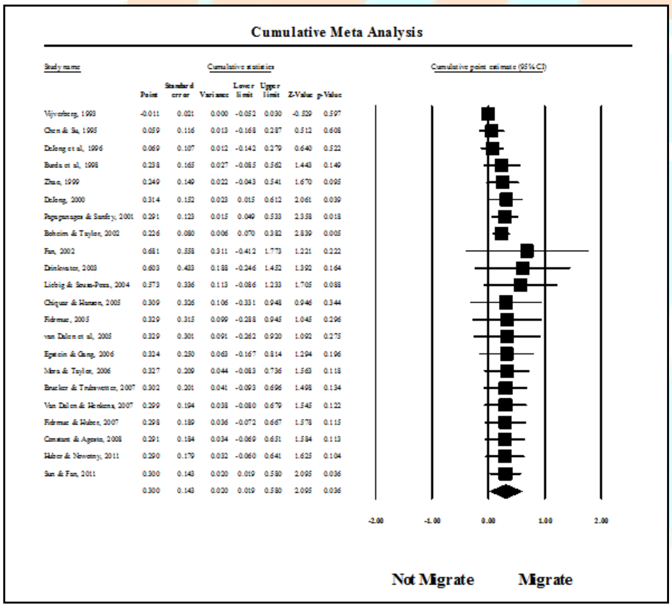

Figure 2. *Cumulative forest plot*

Pane C and Figure 3 reveal two influential studies in the meta-analysis – [17] and [12]. If we omit Fan's study from the meta-analysis, the average coefficient estimate of the education variable on migration behaviour will drop from 0.300 to 0.147. Similarly, if we omit Chiquar & Hanson's study, the average coefficient estimate will increase from 0.300 to 0.394. This finding is not surprising because from Pane A of Table 2, Fan obtained a coefficient estimate of 3.14 for its education variable, while Chiquar & Hanson obtained a negative estimate of 3.537. These two estimates stand out when compared to the others. In this sense, these two influential studies can be regarded as outliers.

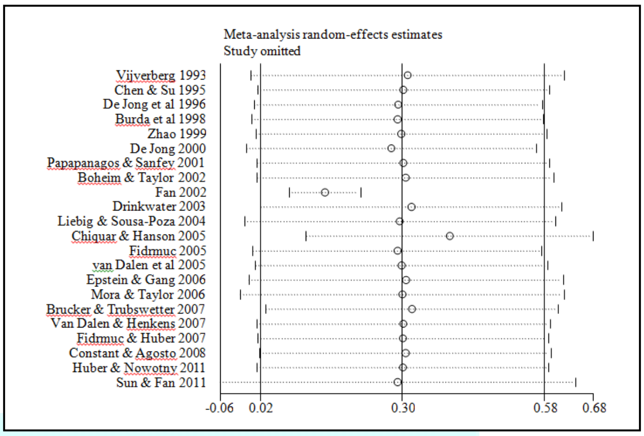

Figure 3. *Influential studies*

B. *Publication Bias*

I also check for publication bias to ensure no significant bias in the 22 studies selected for this meta-analysis (in which 18 are journal articles, 3 working/discussion papers, and 1 book chapter). Publication bias can arise when (i) statistically insignificant results are unpublished or being put away in the file drawer, (ii) publication in reports or working papers are excluded in the meta-analysis, and (iii) only publication in a certain language are taken into consideration.

Figure 4 shows a funnel plot typically used to check for presence of publication bias. A funnel plot is a scatterplot of the coefficient estimates from the studies and their corresponding standard errors. A funnel plot follows the rationale that when the sample size of a study increases, so does the precision of its coefficient estimate (i.e. as measured by the standard errors). In the absence of publication bias, the coefficient estimates will scatter symmetrically, with those from studies with smaller sample size making up the base of the plot, and coefficient estimates from larger studies will funnel up the plot. Publication bias however, is only one of the possible causes of funnel-plot asymmetries [18].

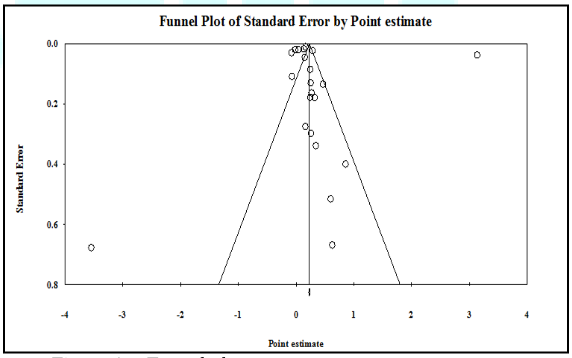

Figure 4. *Funnel plot*

TABLE 2: META-ANALYSIS AND CUMULATIVE META-ANALYSIS

Study	Individual[A]		Cumulative[B]		Study Omitted[C]		
	Coeff	Std err.	Coeff	Std err.	Coeff	95% Confidence interval	
Vijverberg 1993	-0.011	0.021	-0.011	0.021	0.310	0.001	0.620
Chen & Su 1995	0.251	0.179	0.059	0.116	0.302	0.014	0.590
De Jong et al 1996	0.630	0.670	0.069	0.107	0.291	0.008	0.575
Burda et al 1998	0.471***	0.135	0.238	0.165	0.290	0.002	0.579
Zhao 1999	0.346	0.340	0.249*	0.149	0.298	0.011	0.584
De Jong 2000	0.862**	0.401	0.314**	0.152	0.278	-0.008	0.564
Papapanagos & Sanfey 2001	0.260**	0.131	0.291**	0.123	0.301	0.013	0.590
Boheim & Taylor 2002	0.157***	0.046	0.226***	0.080	0.306	0.013	0.599
Fan 2002	3.14***	0.039	0.681	0.558	0.147†	0.076	0.218
Drinkwater 2003	-0.073**	0.031	0.603	0.433	0.317	0.021	0.614
Liebig & Sousa-Poza 2004	0.292***	0.024	0.573*	0.336	0.295	-0.011	0.601
Chiquar & Hanson 2005	-3.537***	0.679	0.309	0.326	0.394†	0.110	0.677
Fidrmuc 2005	0.604	0.517	0.329	0.315	0.289	0.005	0.575
Van Dalen et al 2005	0.330***	(0.180)	0.329	(0.301)	0.298	0.010	0.586
Epstein & Gang 2006	0.047**	(0.021)	0.324	(0.250)	0.307	-0.003	0.617
Mora & Taylor 2006	0.144***	(0.018)	0.327	(0.209)	0.299	-0.020	0.619
Brucker & Trubswetter 2007	-0.068	(0.110)	0.302	(0.201)	0.319	0.030	0.607
Van Dalen & Henkens 2007	0.250***	(0.087)	0.299	(0.194)	0.302	0.013	0.591
Fidrmuc & Huber 2007	0.265	(0.299)	0.298	(0.189)	0.301	0.015	0.588
Constant & Agosto 2008	0.166	(0.276)	0.291	(0.184)	0.306	0.019	0.592
Huber & Nowotny 2011	0.273*	(0.164)	0.290	(0.179)	0.301	0.013	0.589
Sun & Fan 2011	0.169***	(0.011)	0.300**	(0.143)	0.290	-0.060	0.641

Significant at the *10%, **5%, and ***1% level.
† Influential study.
Pane A, B, C.
Using the random-effects approach, the summary effect is computed to be 0.300 with a standard error of 0.143 and a p-value = 0.036.

From Figure 4, there seems to be a bias towards publication with positive coefficient estimates. Formal tests of publication bias however, suggest otherwise. At the 5% significance level, both Egger's test (p-value = 0.586) and Begg's test (p-value = 0.055) suggest no evidence of publication bias. Rosenthal's (1979) classic fail-safe N is 2,642 (a p-value much less than 1%), suggesting that the possibilities are remote for us to have missed out on more than 2,600 studies in the related migration literature. We however, cannot preclude the possibility of language bias since only English-language publications are searched. Nevertheless, it is believed that non-English scholarly publications would not have been significant enough to cause a serious publication bias.

C. *Meta-Regression*

Meta-regression investigates the extent to which statistical heterogeneity between results of multiple studies can be related to one or more characteristics of the studies [19]. It is the best way to account for heterogeneity or between-study variance [20]. Through meta-regressions, observed heterogeneity can be accounted for, in which study characteristics explain some of the variations in the coefficient estimates between the studies. That is, meta-regression can help to answer questions like why some studies obtained positive/negative coefficient estimates, why some of their magnitudes are larger than those of other studies, and why some of the estimates in certain studies are significant while others insignificant. In doing the meta-regression here, we take into account study characteristics as listed in Table 3.

from Figure 1. Had there been no heterogeneity issues, all the squares would have aligned to a straight vertical line.

Results from Table 3 suggest that the source of heterogeneity in the coefficient estimates of the education variable come from six of the study characteristics, i.e. the significant meta-regression coefficients. In running a meta-regression, we are basically estimating the following.

$$b_j = \beta + \sum_{k=1}^{K} \alpha_k Z_{jk} + e_j$$

where,

bj = the reported coefficient estimate of the education variable of the jth study from a total of L studies

β = the 'true' value of the parameter of interest

Z_{jk} = the study characteristics

α_k = the meta-regression coefficient that reflects the biasing effect of particular study characteristics

e_j = the meta-regression error term

j = 1, 2, …, L

The publication year of a study is positively associated with the coefficient magnitude of the original studies, i.e. +0.309; more recent publications found larger positive impact of education on migration intention/decision. This result is also supported by the absence of publication bias discussed in the previous

TABLE 3. STUDY CHARACTERISTICS STATISTICS AND META-REGRESSION COEFFICIENT ESTIMATES.

Characteristic	Defined as	Mean	Meta-Coeff	Std Err.
yrpublish	Year the study is published	n.a.	0.309*	0.138
size	Sample size	6932.14	-0.0001**	0.00004
multispec	Number of model specification examined	3.55	-0.108	0.079
impactfac	Impact factor of publication	0.30	-1.015	0.831
international	1 if examining cross national border migration	0.50	0.300	0.718
actual	1 if dependent variable is on actual migration decision	0.55	-1.243	1.096
logit	1 if a logit model is used	0.32	1.677	1.141
skilled	1 if examining skilled migration or brain drain	0.14	3.986*	2.075
edulevel	1 if the education variable is by education level	0.82	1.658*	0.753
cross	1 if cross-sectional data is used	0.86	-1.107	1.276
student	1 if respondents are students	0.10	-4.906*	2.223
europe	1 if the examined region is in Europe	0.50	-1.628*	0.758
journal	1 if the publication is in an academic journal	0.81	-1.591	0.872

Dependent variable = effect size or the coefficient estimates of the education variable; n.a. = non-applicable; Number of studies, $n=22$. Mean for categorical study characteristics represents the proportion with the characteristic indicated. Significant at the *10%, and **5% level. Study characteristics are also known as moderator variables (Stanley 2001).

Results from the meta-regression indicate presence of heterogeneity in the coefficient estimates, with a between-study variance (or the variance of the true effect sizes) of τ^2=0.836, significant at the 1% level. The proportion of observed variance reflecting real differences in effect size is I^2=99.7%, i.e. 99.7% of the observed variance is due to real differences in the studies rather than to random error. Such heterogeneity is also obvious

focused on obtaining positive and statistically significant results. The fact that we found no evidence of publication bias and that the meta-coefficient shows a significant +0.309, may be pointing to the fact of an increasing impact of education after all. The positive meta-coefficient of the 'skilled' variable (i.e. 3.986) indicates that when a study examines skilled migration or the brain drain phenomenon, the effect size of the education variable increases, resulting in corresponding increases in the probability to migrate. When skilled migration is the issue, the education variable is understandably important and has a significant positive impact on the migration probability of the highly educated. The meta-coefficient of the education variable is +1.658, suggesting that when education level dummies are used in the original studies instead of using years of education, the impact of education on migration intention/decision tends to be positive. One possibility is perhaps the real effect of education is more readily captured by the level of education (i.e. a real difference between the level of a high school diploma and that of a doctoral degree, for instance), than by the years of having been in formal schooling.

At –0.0001, the negative impact of sample size on the coefficient magnitudes is relatively negligible although it has a stronger statistical significance. The negative impact of sample size here suggests that as more respondents are surveyed on their migration intention/decision, the impact of education (i.e. the coefficient magnitude of the education variable) decreases. The negative relationship casts doubts on the presence of genuine empirical effect of the impact of education on migration intention/decision [21]. This result however, could also be due to noise from a heterogeneously large cross-sectional sample. The practical significance of sample size nevertheless remains somewhat trivial. When the migration issue is examined in European region, the impact of the education variable decreases and translates into decreasing probabilities to migrate. This suggests plausibility of easier mobility within the European region, and therefore less importance might be placed on education as a mobility passport. Similarly, when students instead of working professionals are examined, the impact of education on migration behaviour also decreases. The students examined in the original studies are typically foreign students studying in a host country. Since they are already in the host countries, the level of education they are pursuing there is not as important as say other reasons such as assimilation process, insiders' information, and networking, for example. On the contrary, the education level or years of education that working professionals possess might be more crucial in influencing their migration behaviour.

IV. CONCLUSION

This paper may well represent the first meta-analysis application on the impact of education on migration. This is a clear departure from the typical analyses used in the migration literature. Here, we have delineated the standard set-up of the analysis, by first doing a meta-analysis to obtain the summary effect size, followed by a publication bias check, and a meta-regression to identify the source of heterogeneity in effect size. A total of 22 micro-level studies that look at the determinants of migration have been analysed. These papers have included the education variable as one of the regressors, where it is operationalized either as the years of education or the highest level of education obtained. The outcome or dependent variable of these selected studies is either on actual migration behaviour, or on the intention to migrate. The meta-analysis conducted here comprises three parts: the meta-analysis, publication bias check, and meta-regression. Results from the meta-analysis conclude the summary impact of the education coefficient to be approximately +0.300. Results from formal tests on publication bias show no evidence of such bias. A meta-regression is used to account for the source of heterogeneity in the coefficient estimates. Six of the study characteristics are identified to be contributing to the heterogeneity.

An extension of this paper will incorporate coefficient estimates of the education variable from all different model specifications used within a study, instead of only including the coefficient from the base model. Another possible extension is to do a meta-analysis on a vector of coefficients of a number of variables, and not just limited to meta-analysing the impact of the education variable on migration decision.

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