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THE EFFECT OF MIGRATION ON INCOME CONVERGENCE: META-ANALYTIC EVIDENCE*

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Abstract

Using meta-analytical techniques, we focus on 11 studies that explicitly measure the effect of a net migration variable in neoclassical convergence models and derive 57 comparable effect sizes. The data suggest that an increase in the net migration rate of one percentage point increases on average the GDP per capita growth rate by 0.13 percent, thus suggesting a net migration impact that is more consistent with endogenous self-reinforcing growth rather than neoclassical convergence. However, studies that use panel models or IV estimation yield smaller coefficients of net migration while the opposite is the case for regressions controlling for high-skilled migration.

JEL classification: O15, O18, R23, R11

Key words: Internal migration, income convergence, meta-analysis, regional disparities

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**THE EFFECT OF MIGRATION ON INCOME CONVERGENCE:
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1. Introduction

Since the dawn of humankind migration has been an important means through which people can improve their economic well-being and quality of life, either within countries or across borders. The net movement tends to be generally towards prosperous areas which offer higher real income prospects. Geographic mobility has demographic, economic, political, social, and spatial consequences in the receiving and sending regions. Spatial diversity in population growth often coincides with increasing regional disparities. This begs the question of how those who leave and the newcomers in receiving regions affect the distribution of income. This issue has given rise to a significant number of scientific studies across a range of countries. The World Bank's *2008 Urban Growth Report* signals the growing importance of global demographic changes – population ageing, changing internal migration patterns, and cross-border mobility (World Bank, 2008a). The *World Development Report 2009* argues that labour mobility helps to exploit scale economies and may reduce spatial disparities despite increasing economic concentration (World Bank, 2008b).

However, the literature is not conclusive with respect to the consequences of migration on the speed of income convergence. Many researchers emphasize the labour-supply effect of migration in the standard neoclassical framework. Yet many others oppose the standard growth model and point for example to the importance of migrants' characteristics, specifically age and skills. During the last two decades, the economic growth literature has produced a large number of studies that have analysed per capita income convergence. Recently, some attention has been devoted to the role of internal migration in income convergence. Simply in terms of aggregate demand and scale of the economy, regions losing population through migration may face economic contraction, whereas regions gaining population through migration may benefit from an expansionary effect on output, employment and income. However, studies of the consequences of migration show that the transfer of human capital from one place to another is a critical aspect (e.g. Kanbur and Rapoport, 2005; Rappaport, 2005). In particular, skill-selective mobility may have unforeseen impacts on origin and destination places. Not only increased migration levels but also the concentration of migrants in metropolitan areas raises concerns regarding the impact of migration on origin and recipient regions. Fuelled by migration, the global urban population grew from 220 million to 2.8 billion over the 20th century (UNFPA, 2007).

The literature produces a range of conclusions regarding the effects of migration. The observed results may depend on various study characteristics, research methodologies, type of data, and the spatial scale at which the research has been conducted. Additional insight into the quantitative effect of migration may be obtained by analysing the variation in the estimated effect sizes across primary studies. Meta-analytical techniques provide appropriate tools for this. The aim of the present study is therefore to analyse the effect of migration on income convergence by means of a meta-analytic evaluation of various studies that have incorporated migration as an explanatory variable in income convergence.

In Section 2 we present a brief and selective review of empirical studies on the impact of migration on economic growth. Section 3 describes the data obtained from a purposive selection of past studies. A short explanation of our meta-analytical techniques is given in Section 4. We present the results of the meta-regression analysis in Section 5. Section 6 concludes.

2. Impact of Migration on Income Convergence: A Review

Can internal migration contribute to the absorption of external economic shocks in regions and the alleviation of regional inequalities? The neoclassical approach to migration emphasizes how interregional migration can reduce regional income inequality. Income differentials are likely to be self-correcting through migration. As a result of the labour-supply effect, migration should accelerate income convergence (Polese, 1981). Barro and Sala-i-Martin (2004) provide a detailed explanation in the context of the neoclassical growth model. They conclude that, if migration is an important source of convergence and if the endogeneity of migration in growth regressions is corrected by instrumental variables, the estimated beta convergence coefficient (the effect of initial income on growth) should become smaller in regressions that include a migration variable. However, it is not a priori clear whether the coefficient of the migration variable in a growth model would be positive or negative. This would depend, for example, on the extent to which migration affects gross fixed capital formation.

The recent literature has been looking for additional insight into the consequences of migration. Although the neoclassical framework considers labour mobility as the source of spatial income convergence, income levels remain far below their steady state in many regions. The removal of regional disparities through migration and local labour market adjustment takes such a long time that relying exclusively on this adjustment mechanism may lead to underutilization of resources in depressed regions (Pissarides and McMaster, 1990). In addition, Barro and Sala-i Martin (2004) suggest that the effect of migration on convergence between regions (in various countries) is very small. Similarly, Cardenas and Ponton (1995) reported a negligible impact of migration on income convergence in Colombia (1960-1989). Similarly, Gezici and Hewings (2004) find similarly no effect of migration on reducing regional disparities in Turkey (1987-1997). In contrast, Kırdar and Saraçoğlu (2008) detect a strong impact of migration on regional growth rates and on the speed of convergence in Turkey (1975-2000). Such contradictory results warrant a systematic investigation into the causes of different conclusions even for the same country. This is where meta-analysis can play an important role.

The substantial literature opposing the conventional neoclassical framework suggests that both the migratory behaviour and the migrants' characteristics are important in the convergence process (e.g. Greenwood, 1975). For instance, the exit of labour from poorer economies lowers gross fixed capital formation in such regions. Therefore, the disincentive effect of outmigration on investment may dominate the direct effect of outmigration on labour supply and wages, so that outward migration may slow wage growth rather than increase it, as the neoclassical model would predict (Rappaport, 2005).

There are two major impacts of labour migration: the scale (size) effect, and the composition effect. A high level of outward migration of skilled labour may hurt the labour-exporting region and benefit the labour importing region. Furthermore, migration can be persistent and may not die away over time. For example, Williamson (1991) observed that, in the US over the period 1890-1941, the real wage gap between urban and rural areas showed a striking persistence over five decades despite a continuous unidirectional migration flow into urban areas (Reichlin and Rustichini, 1998).

Evidence from many countries suggests that ignoring the heterogeneity of labour may bias the estimates of the effect of migration on growth (Shioji, 2001). The impact of migration on regional inequalities is unclear unless one explicitly considers the skills of the migrants. Migration can play a role as an adjustment mechanism from which all regions benefit, but it can also favour the economy of only the recipient region. Heterogeneous labour may offset the size effect of migration through the change in the ratio between skilled and unskilled workers (Etzo, 2008). Labour flows influence the human capital endowments. Flows of skilled labour can lead to an upward shift in the production of the recipient regions (Fratesi and Riggi, 2007). Indeed, the skills of the migrants determine what happens to the economic opportunities in a source region when a selected subsample of its population moves elsewhere (Borjas, 1999). Decentralized wage determination and tax incentives can play a role in attracting highly-skilled labour.

In the case of an inflow of skilled labour, it is likely that a cumulative process prevails in the host region. Although migration allows workers to maximize their individual utility, it may also have perverse effects at the aggregate level on regional disparities in income per capita, depending on the skills of migrants (Fratesi and Riggi, 2007). However, even if those with the highest skills and best ability are the ones most likely to migrate, some researchers argue that their return or circular migration may assist in generating a positive impact of skilled labour on the less developed areas (Agunias and Newland, 2007).

The endogenous growth theory that includes migration focuses on the importance of human capital for the productivity of migrants. Migrants with higher human capital endowments are expected to search for job-opportunities over wider geographical areas and are clearly more mobile (McCann, 2001). The highly-skilled also tend to possess better information on alternative employment opportunities.

Despite the earlier noted persistence of migration patterns, the volume and direction of migration may eventually change. Certain factors such as agglomeration and relative wage dispersion effects are quite crucial to the impact of migration on receiving regions. Recent trends indicate a massive movement towards cities. The theory of intervening opportunities suggests that opportunities matter more to migrants than distance (Stouffer, 1940). Cities are places where things are happening, and where there are relatively more opportunities. They are also the places that bring people together, and the externalities created by the diversity of people in cities are the drivers of economic growth (Gleaser et al., 1992). While these effects are greatest in big cities, such cities also simply offer more jobs (Molho, 1986). Greenwood and Hunt (1989) confirm that jobs and wages have a considerably higher direct effect on net metropolitan migration of employed persons than location-specific amenities. Of course, while the job market remains an important determinant of migration patterns, the spatial distribution of the quantity and quality of jobs may not provide a full explanation of observed migration patterns. Such patterns may also be based on other locational attributes (Cushing and Poot, 2004). For example, Gallup et al. (1999) concluded that landlocked areas are economically disadvantaged.[1] This again highlights that the spatial patterns and determinants of economic opportunities remain important drivers of labour mobility.

In conclusion, the effect of migration on income convergence remains an ongoing issue in the recent literature. Past empirical studies appear to be contradictory. The challenge is to identify the theoretical framework that is most strongly supported by the data. Meta-analytic techniques provide a systematic analysis of the available empirical evidence. Such techniques permit us to identify the relationships between the measured effects of migration for both destination and sending regions and study characteristics such as data source, scientific method, and the choice of geographical boundaries. We will therefore utilize meta-analysis in this paper to compare the empirical findings quantitatively and to discuss the causes for observed differences in the impact of net migration on economic growth.

3. Selection of Primary Studies and Study Characteristics

Meta-analysis requires the acquisition of a cluster of studies concerned with the same research question and which use a common econometric specification. The search for papers was conducted systematically through software called Harzing's Publish or Perish (linked to Google scholar) and alternative search engines such as EconLit. Besides references,

[1] The 28 landlocked countries outside Europe, containing 295 million people in 1995 are among the poorest in the world.

Harzing's Publish or Perish also reports the number of citations of each document. We used the following keywords: *migration and convergence, labour mobility, internal migration, income convergence.* The literature search checked extensively electronic resources of published articles and unpublished studies, as well as websites of migration-related research institutes, and international organizations. More than 1200 articles were scanned. For the sake of comparability and homogeneity, only papers that used, or built on, the convergence model suggested by Barro and Sala-i Martin, but with the inclusion of a migration variable, were selected. The selected studies for meta-analysis were all dated after 1991.

The paper selection process initially yielded 16 studies with 84 observations. However, comparability problems remained, and five papers were dropped. From the 11 remaining papers, 57 estimates were obtained. The effect sizes are perfectly comparable to each other after some small transformations. A general problem in this literature is the lack of long-term migration data or the reliability of the migration data generally. In some instances, the time period of the migration flows data does not exactly match that of per capita income growth data. This makes it hard for researchers to calculate the effect of migration for various periods, and they therefore tend to report fewer effect sizes. Secondly, the studies that directly assess the effect of migration on income convergence have been fairly recent (from the mid-1990s), and the literature has not yet provided a wide range of comparable studies. The distribution of 57 effect sizes over a range of countries and studies in our meta-analysis is given in Table 1. [2]

Table 1 about here

The primary studies in our meta-analysis all adopt a specific neoclassical convergence model, and the discussions on the effect of migration on income convergence follow the path

[2] Although the following papers, Gezici and Hewings (2004), Maza (2006), Cashin and Loayza (1995), used the same analytical framework, their estimations were not directly comparable. A serious effort has been put into increasing the number of observations. Moreover, an additional search for non-published papers is ongoing for the same purpose.

breaking research by Barro and Sala-i Martin (1992, 2004).[3] There is clearly one regression equation that all the considered studies used in their analysis:

$$(1/T)\ .\ \log(y_{it}/y_{i,t-T}) = \alpha - [(1 - e^{-\beta T})/T].\ [\log(y_{\ i,t-T})] + \gamma m + \text{other variables} + \text{error term}, \qquad (1)$$

where the dependent variable is the average annual growth rate of GDP per capita; $y_{i,t}$ is the per capita real income in region i in year t; T is the time span of the data; and γ is a coefficient of the annual net migration rate, where m is calculated as the average annual flow of net migration (in-migration into region i minus out migration from region i) between the years t-T and t divided by the total population at the beginning of the observation period. Hence, mathematically m=$[(NM_{\ i,t-T,t}/T)/P_{i,t-T}]$. Virtually all studies of beta income convergence (so-named because they aim to estimate β in equation (1)) adopt specification (1) or its linearized equivalent, but many studies among these implicitly assume that $\gamma = 0$. The present meta-analysis focuses specifically on evidence for the case that $\gamma \neq 0$.

In this paper we will therefore address the impact of migration on income convergence as an empirical matter. Hence, in the specification above we have two parameters of interest, β and γ. In the first place, we will focus on the effect of migration on income convergence, i.e. the extent of variation in the estimates of γ across and within studies. We also check how accounting for the net migration rate affects the speed of convergence, β. Moreover, we consider whether the results of Barro and Sala-i-Martin's textbook research has been confirmed by other researchers.[4]

Using the 57 effect sizes obtained from the studies listed in Table 1, the distribution of estimates of γ are predominantly within a range of -1 to 1, clustered around zero, and the mean value is 0.1336. Figure 1 shows the ranked distribution of effect sizes and some descriptive statistics. The mean value suggests a small positive impact of migration on the speed of per capita income convergence. At a mean value of about 0.1, an increase in the

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[3] The foundation for all primary studies is the neoclassical closed economy model of Ramsey (1928), Solow (1956), Cass (1965) and Koopmans (1965). All predict that the per capita growth rate tends to be inversely related to the starting level of output or income per capita (Barro and Sala-i Martin, 1992).

[4] Barro and Sala-i-Martin estimated equation (1) with data on the US, Japan and some European countries.

net migration rate of one percentage point would increase the annual growth rate in real GDP per capita by 0.1 per cent.

Figure 1 about here

As shown in Figure 1, there is a reasonable variation of the effect sizes across the primary studies. The fundamental question is the extent to which the variation in effect sizes across studies is systematic rather than due to random variation. Explaining this variation is not only the main interest in this study, but may also provide additional insight to discussions in the recent migration literature. We explain this variation by utilizing *moderator variables* which tend to be predominantly in the form of dummy variables. These present the characteristics of the primary studies. Various features of the regions where the studies have been conducted may have an influence on effect sizes. For instance, country-specific attributes, time variations, data type used in calculations, or the composition of the migrants can all possibly influence the estimated effect of migration. The moderator variables, indicating the study features, used in the meta-regression analysis are presented in Table 2. Since the variables are in the form of binary dummies, reference categories must be selected and these have been shown by (*). The statistical significance of the effect size variation, as well as the impact of each study feature on the net migration-rate coefficient, is considered with multivariate analysis in Section 5.

Table 2 about here

The second interest of our study is whether the speed of convergence is influenced by accounting for the net migration variable and, if so, to what extent? The unweighted mean values suggest that the inclusion of migration in equation (1) has a very slight effect on the speed of income convergence, beta (β).[5] Without accounting for the migration variable, the average estimate of β is 0.0332. With migration, this decreases to 0.0319. Figure 2 shows the distribution of the effect on beta convergence of including a net migration variable in the regression. The effect varies between -0.04 and 0.02, with the average being slightly positive

[5] For the analysis of the beta coefficients our sample size decreases to 45, since in the Shioji (2001) paper the beta coefficients without net migration rate variable are not reported.

(0.0013). This suggests that the migration variable in the economic growth regressions lowers the beta convergence coefficient slightly, as Barro and Sala-i-Martin (2004) expected. Values of *β* convergence in the considered sample of regressions cluster at between 0.00 and 0.02 (with 0.02 representing the commonly observed 'two percent rule'; see Koetse et al. 2005) However, a paired *t*-test indicates that the mean difference is insignificant, meaning that there is not a statistically significant difference between beta convergence in regressions with and without a migration variable. The effect of migration on the speed of income convergence appears as yet inconclusive. Generally, our results are consistent with the findings of Barro and Sala-i Martin (2004) that the estimates of *β* are income convergence at a rate of about 2-3 percent per year, and that migration plays only a minor role in the convergence story.

Figure 2 about here

4. Analysis of Analyses: A Short Introduction to Meta-analysis

During the last century there has been an explosive growth of empirical research. The research findings on a particular topic may indicate a great variety of conclusions and can be confusing and conflicting about central issues of theory and practice even within the same discipline. Narrative literature reviews may not allow the researcher to distil credible and accurate generalizations from the primary studies (Rosenthal and DiMatteo, 2001). Instead, meta-analysis can give a clearer idea of the variation in findings across the literature and provides systematic details of the studies through coding their varying characteristics, as well as the basis on which the research has been conducted (Lipsey and Wilson, 2001). By means of meta-analysis, it is possible to combine the numerical outcomes from various studies, estimate the accuracy of relationships, and explain the inconsistencies between research findings.

In order to carry out meta-analysis researchers collect many studies on a particular topic. However, these studies may differ in terms of methodologies, data sources, and the accuracy of the results. In general, study characteristics matter for the quality of the meta-analytical results. Heterogeneity (factual or methodological) across studies, heteroscedasticity of effect sizes, and correlation of effect sizes between and within studies can cause problems when doing meta-analysis.[6] Heterogeneity, defined as the 'mean variation among the effect sizes that are collected from primary studies', is a major concern. When the distribution of effect sizes is heterogeneous, then the analysts must look for the reason for the disagreement on the magnitude of the effects among the studies. Moreover, "the more unexplained variance across studies, … , the more uncertain is the meaning of the summary statistics" (Lipsey and Wilson, 2001). Although the unexplained factors driving the variation of effect sizes is of great interest the mean effect size should be clear and interpretable.

Therefore, heterogeneity is handled in two main ways: firstly, by focusing on explaining the variation; and secondly, by analysing the mean effect sizes by making particular assumptions regarding their distribution. The most commonly used method for the first approach is meta-regression which explains the variation of effect sizes in terms of regressors that represent various study characteristics.[7] Secondly, random and fixed effect models predict population effect sizes on the basis of the sample of effect sizes collected from primary studies (Nelson and Kennedy, 2008). The random effects model assumes that underlying effects vary randomly. Hence, there are two sources of variation: within and between-study variance.[8] While the random effects model provides a systematic methodology to manage between- and within-study heterogeneity, the fixed effects model assumes no heterogeneity. In other words, in the fixed effects model, primary studies estimate a fixed population effect. For a fixed effects model, let T_i be the observed effect size, i=1,….,k and $\delta_1=\ldots=\delta_k=\delta$, where δ is a true common underlying effect size. Therefore, a pooled fixed estimator of the effect sizes is calculated as follows:

$$\bar{T} = \frac{\sum_{i=1}^{k} T_i / v_i}{\sum_{i=1}^{k} 1/v_i} \tag{2}$$

[6] For a detailed discussion on data characteristics in meta-analysis, see Nelson and Kennedy (2008).
[7] These descriptors are mostly binary dummy variables.
[8] The common use of this approach refers to the cases where the source of variation cannot be identified (Sutton et al., 2000).

The effect sizes are weighted by their estimated inverse variances, because it is important to take into account the possibility of residual heterogeneity. Ignoring such heterogeneity in calculations would overstate the importance of covariates (Thompson and Sharp, 1999). Finally, to weight the estimated effect sizes with their inverse variances accounts for the precision of the estimated effect sizes in primary studies. The weighted average effect size $\bar{\mathbf{T}}$ has an estimated variance $\bar{v}$, where:

$$\bar{v} = \frac{1}{\sum_{i=1}^{k} 1/v_i} \tag{3}$$

and v_i is the estimated variance of effect size T_i.

The standard random effects model assumes that each observed effect size differs from the population effect size in two ways: first, there is variability due to the subject-level sampling error, known as within-study variance; and, second, there is the random variation of the effect sizes, known as between-study variance. Both are assumed to be normally distributed with a mean zero and variance σ_i^2 and τ_i^2. Algebraically, the model is denoted as:

$$\begin{aligned} T_i &= \delta_1 + e_i; & e_i &\sim N(0, \sigma_i^2); \\ \delta_1 &= \delta + \mu_i & \mu_i &\sim N(0, \tau_i^2) \end{aligned} \tag{4}$$

For the same reason as in the fixed effects model, the estimated effect sizes are weighted with their inverse variances for the precise estimation of the mean effect size. Unlike in the fixed effects model, in the random effects model there are two sources of variation, and therefore the inverse weight of each effect size will be equal to $1/(v_i + \tau_i^2)$. In this case v_i represents the within-study variance, and τ_i^2 denotes between-study variance.

Our results for the pooled fixed effects and random effects estimates of the mean coefficient of net migration in growth regressions are given in Table 3. The pooled estimates are statistically significant at the 1% level. As a result of different weight assignments, the larger confidence interval provided by the random effects estimator is rather expected. The weighted mean effect sizes are close to the unweighted mean value of the net migration coefficients. The fixed and random effects model weighted mean effect sizes may differ substantially if the studies are markedly heterogeneous (Egger et al., 1997b). Since the effect sizes are collected from various studies, we run a homogeneity test to check whether "the studies can reasonably be described as sharing a common effect size" (Hedges and Olkin 1985). In the literature by far the most commonly used homogeneity statistic is the Q-statistic (Engels et al., 2000).[9]

Table 3 about here

Before the detailed explanations and results of the Q-statistic are reported, the weighted analysis of the speed of convergence will be given. The pooled fixed effects estimate of beta convergence in regressions that do not consider migration is substantially higher than the corresponding estimate in regressions that do include migration. In formal terms, $\beta_{f1} > \beta_{f2}$ and is significant at the 1% level. The pooled random effects estimations do not indicate the same large difference, although again $\beta_{r1}>\beta_{r2}$ and the difference is significant at the 1% level, despite the larger confidence intervals compared with the fixed effects estimator. In summary, we conclude that, with the fixed and random effects models, migration lowers the speed of convergence (See Table 4).

Table 4 about here

The Q-statistics, however, informs us only about the presence or absence of heterogeneity, and it does not describe the degree of heterogeneity.[10] A generic calculation of the *Q*-statistic is:

[9] This test is devised by Cochran (1954) and based on a chi square that is distributed with *k*-1 degrees of freedom, where *k* stands for the number of effect sizes (Shadish and Haddock, 1994).

[10] "Not rejecting the homogeneity hypothesis usually leads the meta-analyst to adopt a fixed-effects model because it is assumed that the estimated effect sizes only differ by sampling error. In contrast, rejecting the homogeneity assumption can lead to applying a random-effects model that includes both within- and between-studies variability. A shortcoming of the *Q* statistic is that it has poor power to detect true heterogeneity among studies when the meta-analysis includes a small number of studies and excessive power to detect negligible variability with a high number of studies" (Huedo-Medina et al., 2006).

$$Q = \sum_{i=1}^{k} \left[\left(T_i - \overline{T}. \right)^2 / \left(v_i \right) \right] \tag{5}$$

"If [the] *Q*-value is higher than the upper-tail critical value of chi-square at k-1 degrees of freedom, the observed variance in study effect sizes is significantly greater than what we would expect by chance if all studies share a common population effect size" (Shadish and Haddock, 1994). Our *Q*-statistics calculation is equal to 221.0 with 56 degrees of freedom, where the null hypothesis of homogeneity is conclusively rejected with a *p*-value of less than 0.001. Meta-regression analysis is one way to account for heterogeneity systematically. This method will be discussed in the Section 5.

Publication bias is another highly debated topic in meta-analysis. The question is whether the effect sizes are representative of the population concerned. In general, authors are more likely to report significant results, and what is called the 'file-drawer problem' points out that the insignificant results are more likely to be buried in the filing cabinet, although the quality of the research may be high. Moreover, publishers are more likely to publish statistically significant results than insignificant results (Begg, 1994; Rosenthal and DiMatteo, 2001). Doing a meta-analysis by means of a sample which suffers from biased selection of studies and estimates may have serious consequences for the interpretation of the statistical inference. In meta-analysis there is also the possibility of an inherent bias due to the selection of only a *cluster* of studies, the common methodology these studies use, and the common language in which the papers were written. One way to deal with publication bias is to use a weighting technique that quantifies the methodological strength of each study in the analysis (Rosenthal and DiMatteo, 2001).

In Figure 3 the effect sizes are plotted against their standard errors for a measure precision. Along the vertical axis we measure the standard errors of the effect sizes, while the effect sizes themselves are measured along the horizontal axis. The broken lines indicate the expected 95% confidence intervals for a given standard error, assuming no heterogeneity between studies. One should, however, be cautious that publication bias is only one of the possibilities that distribute funnel plot asymmetrically (de Dominicis et al., 2008). In our calculations of Egger's regression test (Egger et al., 1997a), as the constant is significantly different from zero, this provides evidence for publication bias. In our case, the observations are distributed symmetrically, with positive effects being overrepresented, although the coefficient of bias is 0.147 with an associated p-value of 0.614. Hence publication bias is statistically insignificant with the present data.

Figure 3 about here

5 Meta-Regression Analysis

5.1 Methodology

Meta-regression analysis is a major statistical technique that integrates effect sizes gathered from various independent studies and explains the variation in them. This variation may come from two different sources: as a result of sampling error (that may vary across studies) or due to variability in the population of effects: namely, unique differences in the set of true population effect sizes (Lipsey and Wilson, 2001). The former variation in the random effects model causes inherent heteroscedasticity in the meta-analysis sample, while the latter causes randomness of effect sizes from misspecified primary studies. Moreover, using a standard OLS estimation to explain the heterogeneity leads to inefficient results since the effect sizes with a higher variance will get the same weight as effect sizes with a lower variance (Koetse et al., 2007)

The meta-analytical techniques provide econometric insights based on particular assumptions to address these problems. A very common practice, the fixed effects regression model, assumes that the variation among the effect sizes is fully predictable by a number of moderator variables gathered from the primary studies. In general, the fixed effects estimator is also known as the 'inverse variance-weighted' method, where the weights are inversely proportional to the precision of the estimates, and the estimation is predicted by weighted least squares (WLS). A linear fixed effects model is as follows (Sutton et al., 2000):

$$\theta_i = \beta_0 + \beta_1\chi_{i1} + \dots\dots\dots + \beta_p\chi_{ip} + \varepsilon_i \qquad \varepsilon_i \sim N(0, \sigma_i^2), \qquad (6)$$

where θ_i refers to effect size *i*, *p* denotes the number of moderator variables χ_{ip}; and the βs are the coefficients to be estimated. The weights can easily be calculated by the reciprocal of the sampling variances (weight for T_i: $w_i = 1/v_i$), and the coefficients are predicted via WLS (Hedges, 1994).[11] In standard statistical packages, the coefficients are correctly estimated with WLS, but the standard errors are estimated by means of a slightly different formula than in the fixed effects model, hence an adjustment is required. $S_j = SE_j/\sqrt{MS_{error}}$ adjusts the reported standard errors; S_j is the corrected standard error; SE_j is the standard error of the coefficient; and MS_{error} is the mean squared error from the analysis of variance for the regression.

In general, the mixed effects model is considered as a combination of the meta-regression model and the random effects model (Sutton et al., 2000). Different from the fixed effects model, the mixed effects model allows for two variance components. The mixed effects model assumes that the effects of between-study variables (subject-level sampling error), such as the type of data a study uses, are systematic, but that there is an additional component that remains unmeasured (and is possibly unmeasurable). The latter represents a random effect in the effect size distribution, in addition to sampling error (Lipsey and Wilson, 2001).

$$\theta_i = \beta_0 + \beta_1\chi_{i1} + \dots\dots\dots + \beta_p\chi_{ip} + \varepsilon_i + \mu_i \qquad \varepsilon_i \sim N(0, \sigma_i^2), \quad \mu_i \sim N(0, \tau_i^2). \tag{7}$$

As indicated in Equation (7), there are two error components referring to the within- and between-study variances, respectively. These are additively included in the equation and hold for the weights in random variances. As a result of including a random variance component in the error formulation, the level of statistical significance and the confidence intervals may change (Lipsey and Wilson, 2001), in particular widen, and thus increase uncertainty with respect to the estimate of the population mean. Estimation is based on an iterative maximum likelihood estimator.

[11] Weighted Least Squares can account for selection bias, non-normality and heteroscedasticity. Heteroscedasticity results in inefficient estimators, biased standard errors, and faulty t-test values, and unreliable confidence intervals. In WLS, the original heteroscedastic equation is transformed into a homoscedastic equation, an equation with a constant error variance. WLS is also known as variance stabilizing transformation. It is the process of minimizing the influence of a case with a large error. Therefore, the transformed random error term is expected to have a mean zero and constant variance.

Each of the studies selected for meta-analysis usually do present multiple effect sizes. Therefore, the studies with a high number of effect sizes may dominate the prediction of the overall mean effect size. Assigning a within-study weight summed to 1 is a common instrument used to overcome this problem (Nelson and Kennedy, 2008). By using this instrument we give equal weight to each study, though the impact of individual effect sizes varies.[12]

In meta-analysis there are several statistical techniques that exist to combine the effect sizes, yet there is no single "correct" method. Most frequently, sensitivity analysis is required to assess the robustness of combined estimates to different assumptions and other criteria (Egger et al., 1997b). The empirical results of meta-regression analysis are given in the following sub-section.

5.2. Empirical Results

We saw from Table 2 that the mean estimate of the migration coefficient varies across a number of study characteristics: level of development of the country, type of data, etc. By looking at the differences in mean estimates, we may get some idea about which study characteristics matter (Abreu et al., 2005). We used meta-analysis to check whether such study characteristics affect the mean effect size in a statistically significant way. The results of the meta-regression model using different estimators are given in Annex II. Since we have a modest number of observations, we aim to formulate a straightforward model that brings further insights to methodological and empirical discussions. We report our results by using three estimation techniques that are discussed in detail in Section 4. These are OLS, WLS, fixed effects and mixed effects models. Varying the estimators provides a sensitivity analysis that allows us to identify the robustness of the results. There is, in general, a uniformity of results, although the mixed effects technique, which contains two error terms in its underlying hypothesis, deviates somewhat from the other two estimators. It is not realistic to expect meta-analysis to explain the entire variation that exists in the data (Nelson and Kennedy, 2008). The outcome of empirical testing cannot be predicted beforehand, precisely because the sources of influence on the outcome are both numerous and sometimes

[12] This is denoted by WLS^1 in Table 5.

unidentifiable (Raudenbush, 1994). Accordingly, while interpreting the results one should remember the basic assumptions of the estimation techniques.

Heterogeneity in data selection is an important issue that may influence the results of meta-analysis. In general, there is a consensus that using regional scale data is more homogenous in comparison to cross-country data in terms of the technology of the corresponding economies (Barro and Sala-i Martin, 1992: Abreu et al., 2005). We may then expect that regional data are implicitly generating more migration homogeneity as well. In countries where regional disparities are very high, however, some additional testing such as outlier analysis may be required. The influence of observations from particular countries, as well as from studies should be controlled for. In this study we use two different weighting techniques to address these matters.

There are two more important econometric issues in the migration and growth literature: simultaneity bias, and omitted variable bias (OVB) (Kırdar and Saraçoğlu, 2008). As discussed in Section 2, the areas with higher than average real wage growth are expected to exhibit relatively strong net in-migration flows. There is a two-way causality between growth and migration. Therefore, OLS may generate biased estimates. For this reason, estimation technique is important, and the use of *two stage models* is highly recommended in the literature. Our results suggest that IV estimation leads to a smaller positive effect of migration on real income growth compared with the other estimation techniques. This result is highly significant in all estimation techniques (but see also Table 2 for the simple averages).

Secondly, in the presence of omitted variable bias (OVB), there is a correlation between unobserved regional characteristics and growth. Using a panel structure with regional fixed effects is one way in which researchers can overcome OVB (as long as the omitted variable is cross-sectional rather than temporal). Hence, the panel data methodology controls for time-invariant structural differences across the regions (Cashin and Loayza, 1995; Etzo, 2008). Our findings indicate that using pooled data has a negative significant effect on the migration effect on growth. Therefore, if unobserved heterogeneity is not accounted for, it is likely that the effect of migration is overemphasized, implying that it is estimated higher than its actual impact. Our findings confirm this expectation. The results suggest an upward bias in the migration effect on income convergence with cross-section data.

The heterogeneity of migrants is an important recent issue in the literature. The skill composition of the migrants may directly affect the impact on host regions (Etzo, 2008; Shioji, 2001). Highly-skilled migrants are expected to have a stronger positive impact on growth than lesser-skilled migrants. They are also more mobile. The steady state of the labour market is partly determined by the human capital, so human capital is expected to lead to a higher estimate of the rate of convergence. Researchers are increasingly questioning the measurement of migrants' skills and suggesting that gross migration rates should be studied rather than net migration rates because of *asymmetric effects* of skills on inward and outward migration. It is therefore important to consider those studies that have controlled for the composition of migrants.[13] In our meta-analysis we accounted for the composition effect of migrants with a migrant-skill dummy. Our regression results confirm the importance of recent discussions regarding the effect of migrant composition. The coefficient of skilled migrants is positive and higher in all estimations, although the mixed effects result is less informative. In summary, studies that ignore the human capital composition of the migration flows find a smaller coefficient of migration in the growth regression that studies than explicitly account for the skills of the migrants.

Various covariates may be included in regressions of the impact of migration on real income growth to avoid omitted variable bias. Sectoral composition and per capita public investment are among the most frequently used covariates. Sudden changes in the sectoral structure of a particular region may have an adverse effect on the growth of the region. The sectoral composition variable provides a measure of how the endowment of industries in a region affects overall growth (i.e. whether sunrise or sunset industries are overrepresented: Cardenas and Ponton, 1995). The effect of the inclusion of sectoral composition on the migration coefficient is negative and insignificant in all estimations, except fixed effects estimation[2] (see Table 5).

[13] The human capital content of a worker (i.e. employed migrant) with a low educational attainment, but with a sufficient level of work experience, is likely to be underestimated when only the educational attainment is taken into account. The data problem is a major obstruction to further analysis on these lines.

Table 5 about here

Similarly, the inclusion of per capita public investment also has a negative effect, albeit insignificant in all estimations, again except fixed effects estimation [2]. However, if we allow for a random component, the impact of conditioning variables on the effect of migration in the growth regression turns insignificant.

In measuring the consequences of migration, it is important to allow for exogenous shifts and other trends such as technological improvements. Such forces could create temporary or permanent migratory waves. In such cases, it would be wise to consider a time dummy in the primary growth regression since the estimate of the migration impact on convergence may otherwise be biased.[14] We found a significant effect for studies that allowed for time dummies at the 1% level, but only when we assigned equal weight to each study in our database. If we control for time dummies, we find a lower migration coefficient than otherwise in both fixed effects[2] and mixed effects models.

Finally, we expect that the broad level or phase of development may have an impact on the growth regressions. We may expect that in developing countries migration would be more homogeneous than in developed countries.[15] It is difficult to measure the impact of these differences, since statistically the spatial dimension of migration patterns has only recently appeared on the research agenda. However, in our database none of the papers appeared to incorporate the spatial dimension of migration into their growth analysis. Nevertheless, in order to measure the spatial aspect of migration, we applied a country dummy 'development', referring to the development level of the countries in our sample. Therefore, the countries, although to some extent general, are categorized as developed and developing. The results suggest that, migration leads to a higher positive effect on

[14] Another important issue with time dummies is the possible bias caused by the author simply not taking these shocks into consideration during his analysis of migration. In such cases, the researcher may need to go beyond the primary study and check for the possible exogenous effects.

[15] The migration that takes place in the developing world is dominantly in the form of rural-urban flows, a pattern which is especially sustained in South and East Asia, while migrants of the developed world have a tendency to move between the countries in the same part of the world and are looking opportunities to emerge from the benefits of agglomeration (World Bank, 2008b).

convergence in a developed country than in a developing country, although the coefficient is not statistically significant.

6. Conclusion

In this study the issues of comparability and combinability of evidence, which need to be considered in any review, have been made explicit. The study analysed the impact of migration on income convergence by applying several meta-analytical techniques. Meta analysis is utilized to provide a quantitative methodological description for, and measure of, effect size heterogeneity that exists across the primary papers. For the meta-analysis various published and unpublished studies that assessed the role of migration in income convergence were collected. The variation in the reported effect sizes of the net migration rate effect on real income growth is explained by means of various estimation techniques. The results from these techniques are rather consistent.

As a result of synthesizing the empirical work, we conclude that the overall effect of migration on income convergence is positive but quite modest. Consequently, we find that net inward migration coincides with faster economic growth. This conclusion is consistent with the perspective of the new endogenous growth theories rather than with the neoclassical model with homogenous labour (Fingleton and Fischer, 2008). However, in line with neoclassical predictions, the β coefficient of income convergence decreases once migration is included in the growth equation as an explanatory variable. However, this effect is very small. At a mean value of about 0.1, an increase in the net migration rate of one percentage point would increase the annual growth rate in real GDP per capita by 0.1 per cent. Our results indicate that controlling for the migrant characteristics - high skilled migrants - increases the effect of migration on convergence. However, assessing the composition effect of migration remains a subject for more detailed analysis.

Comparatively analysing the papers leads us to conclude that in many countries data problems are a common difficulty for the researchers. The available data to some extent drive the research methodology used in the papers. Furthermore, our results suggest that the type of the data has a significant influence in predicting the migration effect on convergence. Secondly, the results indicate a clear point about the research methodology;

that two-stage estimation techniques are efficient tools to overcome two-way causality problem between migration and growth. The IV method reveals a lower of migration effect on income growth.

Controlling for the exogenous shifts by means of explanatory variables did not reveal a significant effect. Hence, it matters to select efficient explanatory variables. The effect of different geographies in explaining the consequences of migration on convergence is not significant. The spatial analysis of migration and its effects on income convergence still requires in-depth attention. In our model, there are basically two variables (type of the data and type of the estimator) that present results which are robust across the different estimation techniques and with respect to effect size. In general our findings are consistent with the theoretical explanations.

As a result, the findings imply that the theoretical arguments are relevant to the empirics. Therefore, the insights from the economists stress the need for policy makers to rethink the policy implications of migration. The perceived impact of migration and the mainstream beliefs about its consequences are not sustained by the empirical findings of the literature.

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Table 1. Primary Studies used in Meta-analysis

Study id	Study key	Reference	No. of estimates	Country
1	ks (2007)	Kırdar and Saraçoğlu (2008)	2	Turkey
2	e (2008)	Etzo (2008)	6	Italy
3	cp (1995)	Cardenas and Ponton (1995)	3	Colombia
4	s (2001)	Shioji (2001)	12	Japan
5	bs (1992)	Barro and Sala-i-Martin (1992)	3	US and Japan
6	st (2004)	Soto and Torche (2004)	1	Chile
7	p (1997)	Persson (1997)	8	Sweden
8	thm (2004)	Toya, Hosono and Makino (2004)	2	Philippines
9	p (2008)	Peeters (2008)	2	Belgium
10	ow (2007)	Ostbye and Westerlund (2007)	4	Norway and Sweden
11	bs (2004)	Barro and Sala-i-Martin (2004)	14	US, Japan and EU5
Total number of observations			57	

Table 2. Descriptive statistics

Study Characteristics		N	Mean	Std. Dev.	Min.	Max.
Level of development	developing country (*)	8	0.1819	0.7204	-1.2500	1.1000
	developed country	49	0.1257	0.2872	-0.5420	0.7970
Type of the data	cross-section (*)	17	0.2678	0.3528	-0.4060	0.7970
	pooled	40	0.0766	0.3647	-1.2500	1.1000
Type of the estimator	other estimators (*)	37	0.1650	0.2870	-0.4440	1.1000
	IV	20	0.0755	0.4890	-1.2500	0.7970
Time dummies	not accounted for (*)	50	0.1013	0.3416	-1.2500	0.7970
	accounted for	7	0.3641	0.4953	-0.4440	1.1000
Conditional variables	not used (*)	18	0.1777	0.4650	-1.2500	0.8350
	used	39	0.1132	0.3198	-0.5420	1.1000
Migration of highly skilled workers	not accounted for (*)	46	0.0950	0.3559	-1.2500	1.1000
	accounted for	11	0.2950	0.3949	-0.4060	0.7970
Total Sample		57	0.1336	0.3687	-1.2500	1.1000

(*) stands for reference categories in the regression analysis.

Table 3. The Fixed and Random Effects Estimations of Net Migration

Method	Pooled Est	95% CI Lower	95% CI Upper	Asymptotic z_value	Asymptotic p_value	No. of studies
Fixed	0.091	0.084	0.097	26.787	0.000	57
Random	0.098	0.067	0.129	6.155	0.000	

Test for heterogeneity: Q= 221.000 on 56 degrees of freedom (p= 0.000)
Moment-based estimate of between studies variance = 0.004

Table 4. The Fixed and Random Effects Estimations of Coefficient β_1 and β_2

Method	Pooled Est	95% CI Lower	95% CI Upper	Asymptotic z_value	Asymptotic p_value	No. of studies
Fixed	0.029	0.029	0.030	72.537	0.000	45
Random	0.030	0.028	0.033	23.290	0.000	

Test for heterogeneity: Q= 244.538 on 44 degrees of freedom (p= 0.000)
Moment-based estimate of between studies variance = 0.000

Method	Pooled Est	95% CI Lower	95% CI Upper	Asymptotic z_value	Asymptotic p_value	No. of studies
Fixed	0.004	0.004	0.004	43.429	0.000	45
Random	0.028	0.024	0.032	13.314	0.000	

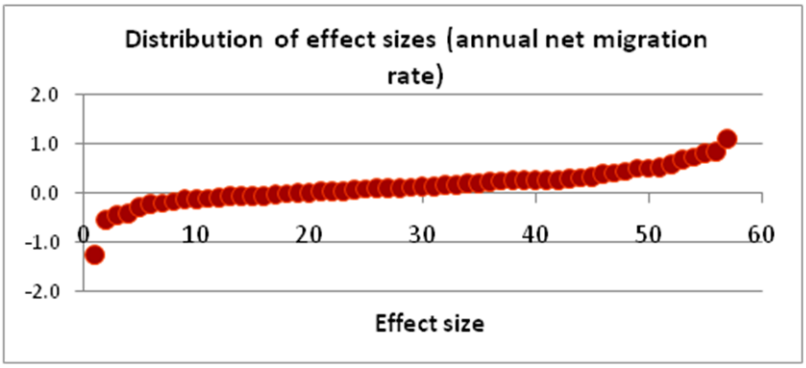
Test for heterogeneity: Q= 3074.932 on 44 degrees of freedom (p= 0.000)
Moment-based estimate of between studies variance = 0.000

Table 5. Results of multivariate analysis

Study Characteristics		OLS	WLS [1]	Fixed Effects[2]	Mixed Effects
Development	developed	0.0972	0.1321	0.0983	0.1565
		(0.1528)	(0.1287)	(0.0947)	(0.1122)
	developing (†)	-	-	-	-
Type of the data	pooled	-0.3001**	-0.3473***	-0.3009***	-0.3218***
		(0.1273)	(0.1139)	(0.1070)	(0.0824)
	cross-section (†)	-	-	-	-
Type of the estimator	IV	-0.2361**	-0.4763***	-0.1197*	-0.1273*
		(0.1146)	(0.1302)	(0.0678)	(0.0720)
	others (†)	-	-	-	-
Time dummies	accounted for	0.3418**	0.4135***	0.1704	0.1689
		(0.1515)	(0.1311)	(0.3058)	(0.1876)
	not accounted for (†)	-	-	-	-
Conditional variables	used	-0.0121	0.0035	0.0565***	0.0030
		(0.1062)	(0.1124)	(0.0177)	(0.0643)
	not used (†)	-	-	-	-
Migration of highly skilled workers	accounted for	0.1864	0.3649**	0.1489*	0.1237
		(0.1348)	(0.1663)	(0.0885)	(0.0877)
	not accounted for (†)	-	-	-	-
Constant		0.2738*	0.2337*	0.2439**	0.2400**
		(0.1537)	(0.1213)	(0.1209)	(0.0999)

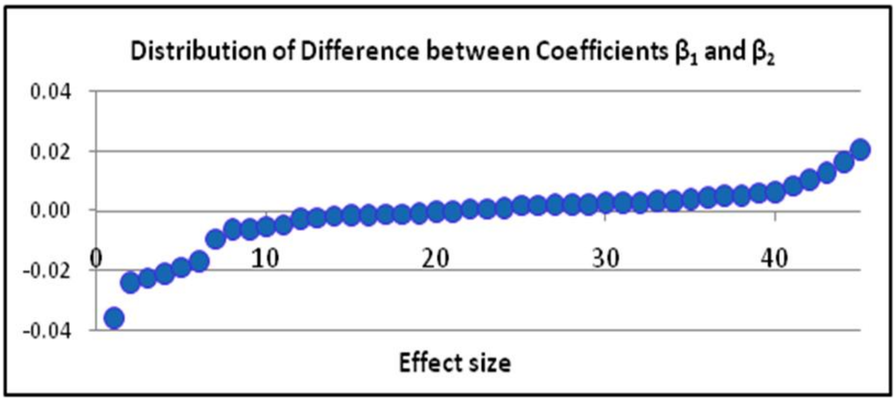
(†) stands for reference categories in the regression analysis
Standard errors are given in parenthesis. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. The standard errors are given in parentheses; WLS[1]: equal weight '1' is assigned to each study in the database; Fixed effects[2]: weighted by the inverse squared standard error of the effect sizes.

Figure 1: Distribution of Effect Sizes



Statistics	Net migration
N	57
Mean	0.1336
St.dev.	0.3687
Min	-1.25
Max	1.1

Figure 2. Distribution of Coefficients β1 and β2



Statistics	β1	β2
N	45	45
Mean	.0332	.0319
Median	.0302	.0268
St.dev.	.0162	.0173
Min	.0082	.003
Max	.0798	.0818

Figure 3. Funnel plot for publication bias