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The effect of migration on income growth and convergence: Meta-analytic evidence*

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Abstract. We compare a set of econometric studies that measure the effect of net internal migration in neoclassical models of long-run real income convergence and derive 67 comparable effect sizes. The precision-weighted estimate of beta convergence is about 2.7 per cent. An increase of one percentage point in the net migration rate of a region increases the per capita income growth rate in that region on average by about 0.1 percentage points. Introducing a net migration variable in a growth regression increases the estimate of beta convergence slightly. Studies that use panel models or IV estimation methods yield smaller coefficients of net migration in growth regressions, while the opposite holds for regressions controlling for high-skilled migration.

JEL classification: O15, O18, R23, R11

Key words: Internal migration, economic growth, convergence, meta-analysis, neoclassical model, regional disparities

1 Introduction

Migration is an important means through which people can improve their economic well-being and quality of life. In general, net population movement tends to be oriented towards prosperous areas which offer higher real income prospects. Fuelled by migration, the global urban population grew 12.7 times in the 20th century (UNFPA 2007), while the world population increased

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by about a factor of four (UN 2009).[1] The concentration of population in particular cities and regions often coincides with increasing regional disparities within countries due to agglomeration effects (e.g., Fujita and Thisse 2002). This prompts the question how those that leave a region, and thereby become a newcomer in a migrant receiving region, affect the spatial distribution of income. The redistribution of population across cities and regions invokes a wide range of short-run and long-run supply effects and demand effects of which the joint impact is ultimately an empirical matter. Our study focuses therefore on the consequences of net internal migration for spatial disparities in economic growth, and for the speed of income convergence.

Many researchers emphasize the labour-supply effect of migration in a standard neoclassical framework. Migration is in this framework a mechanism for reducing spatial income differentials (e.g., McCann 2001). Yet many others oppose the standard growth model, and point, for example, to the importance of migrants' characteristics such as youthfulness, entrepreneurship and skills that, together with their impact on aggregate demand, may have growth-enhancing effects, particularly in an agglomerated economy (e.g., Poot 2008). 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 on the consequences of migration show that the transfer of human capital from one place to another is a critical aspect (see Kanbur and Rapoport 2005; Rappaport 2005). In particular, skill-selective mobility may have profound impacts on origin and destination places, a finding that may be at odds with a neoclassical framework.

Since the 1990s, the economic growth literature has produced a number of studies that have analysed the role of internal migration on per capita income convergence. The evidence produced by the current literature regarding the effects of migration is not yet conclusive. The observed results may depend on various study characteristics, research methodologies, type of data, and the spatial scale of measurement at which the research has been conducted (Nijkamp 2009). Additional insight into the quantitative effect of migration may be obtained by analysing the variation in the estimated regression coefficients across a range of primary studies. Meta-analytical techniques provide appropriate tools for this research task. 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 econometric studies that have incorporated migration as an explanatory variable in regression models of 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 a short explanation of our meta-analytical technique. The data obtained from a purposive selection of past empirical studies is given in Section 4. We present the results of our meta-regression analysis in Section 5. Section 6 offers concluding remarks.

2 Impact of migration on income convergence: A review

Can internal migration contribute to the absorption of external economic shocks in regions and to the alleviation of regional inequalities? An extension of the Solow-Swan model of growth in a composite good economy that incorporates migration of homogeneous labour shows that as long as there are diminishing returns to labour, workers move from low income to high income regions, and migrants have on average low levels of human capital, migration accelerates income convergence (e.g., Barro and Sala-i-Martin 2004). When there are no barriers to factor

[1] The global urban population grew in this period from 220 million to 2.8 billion, while the world population grew from 1.7 billion to about 6.8 billion.

mobility, labour and capital move in this model in opposite directions and both contribute to a reduction in spatial disparities in capital per effective unit of labour, as well as income per capita. Migration in the form of a movement of labour from poor to rich areas lowers capital intensity (increases the return to capital) in the destination region, and increases capital intensity (lowers the return to capital) in the region of origin. Thus, when the same technologies are used everywhere, migration speeds up per capita interregional convergence in capital intensity and income (Polese 1981).

Barro and Sala-i-Martin (2004) provide a detailed explanation of this phenomenon 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 controlled for, the estimated beta coefficient (the effect of initial income on economic growth during the transition to the steady-state growth path) should become smaller in regressions that include a migration variable. In addition, in a world in which the same composite good is produced everywhere with the same technology with homogeneous labour, increasing population growth through net inward migration lowers the rate of economic growth (growth in income per capita). The coefficient of the migration variable in a growth regression, when properly instrumented to account for endogeneity, would then be negative.

Both labour mobility and capital mobility will bring the capital intensities of sending and receiving regions closer, which is the mechanism through which factor mobility contributes to interregional income convergence. Clearly, the impact of net migration on convergence and growth will, in practice, depend on interregional differences in capital intensity, the skill levels of the migrants, the extent to which migration induces gross fixed capital formation, the composition of output and the associated technologies, and the extent to which migration affects technological change (e.g., McCann 2001; Nijkamp and Poot 1998).

If out-migrants possess on average substantially higher human capital than stayers, it will take longer for sending economies to reach their long-run steady state. Additionally, the exit of labour from poorer regions may lower 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 down wage growth rather than increase it as the neoclassical model would predict (Rappaport 2005). If net inward migration increases real per capita income growth, then this creates a self-reinforcing growth process and possible divergence. If beta convergence is nonetheless a feature of long-run development, it must be strong enough to offset an income-enhancing net migration effect. The presence of a significantly positive net migration variable in a growth regression is then expected to increase the estimate of beta convergence (i.e., remove the negative omitted variable bias in estimates of beta in regressions without the migration variable). Which of the two cases (negative net migration effect with positive omitted variable bias in the estimate of beta convergence versus positive net migration effect with negative omitted variable bias in the estimate of beta convergence) is more plausible is ultimately an empirical matter.

The following econometric specification is commonly used in the literature to measure the impact of migration on economic growth and convergence:

$$(1/T).\log\left(y_{r,t}/y_{r,t-T}\right)=\alpha-\left[\left(1-e^{-\beta T}\right)/T\right].\left[\log\left(y_{r,t-T}\right)\right]+\gamma m_{r,t}+\text{other variables}+\text{error term}, \tag{1}$$

where the dependent variable is the average annual growth rate of per capita income; $y_{r,t}$ is the per capita income in region r in the 12 month period ending at date t; T is the number of years spanned by the data; β is the annual rate at which an economy converges to its own long-run steady state, and γ is the coefficient of the annual net migration rate $m_{r,t}$. This rate is calculated as the average annual net migration flow (in-migration into region r minus out-migration from region r) between date $t-T$ and date t, divided by the total population at date $t-T$. Mathematically, $m_{r,t} = [(NM_{r,t-T,t}/T)/P_{r,t-T}]$. Virtually all studies of beta income convergence (so-named, because these studies 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 on evidence that explicitly tests that $\gamma \neq 0$. The coefficient of interest is therefore γ, the coefficient of the net migration variable. In the neoclassical model we would expect that $\gamma < 0$ once we can treat migration as exogenous with respect to the error term. We also expect that regressions that *impose* that $\gamma = 0$, while in fact $\gamma < 0$, show a greater effect of initial income on growth, namely, a greater β (Barro and Sala-i-Martin, 2004, p.492). The bias in the estimation of β due to the omitted net migration variable is then positive. We will use β_o to refer to an estimate of β when net migration rate variable is omitted, and β_i to refer to an estimate of β when the net migration variable is included. When the net migration rate variable is estimated to be negative (the neoclassical case), then we expect $\beta_o - \beta_i > 0$; but when the estimated coefficient of net migration is positive, then we expect $\beta_o - \beta_i < 0$. The empirical analysis reported in Section 4.3 confirms this intuition.

Various studies on the effect of internal migration in the neoclassical growth model have yielded diverse results. Barro and Sala-i Martin (2004, Table 11.7) find that the effect of internal migration on growth in per capita income across regions in the US, Japan and various European countries is statistically insignificant once instrumental variables account for endogeneity of net migration. The effect on the estimated β is inconclusive as well.[2] Similarly, Cardenas and Ponton (1995) report a negligible impact of migration on income convergence in Colombia (1960–1989), and Gezici and Hewings (2004) find no effect of migration on reducing regional disparities in Turkey (1987–1997). In contrast, Kırdar and Saraçoğlu (2008) detect a negative impact of migration on regional growth rates and a decrease in the estimate of beta convergence in Turkey (1975–2000). Such apparently contradictory results, even for the same country, warrant a systematic investigation into the causes of such differences in conclusions. Meta-analysis has the potential to add scientific value to existing studies by uncovering statistically significant pooled effects where the individual studies are inconclusive or inconsistent. The present paper provides an excellent example of this benefit of meta-analysis.

A substantial literature has emerged to consider the very slow convergence, convergence only within clusters or 'clubs', or divergence observed in reality (see, e.g., Islam 2003 for a review of the literature). The removal of regional disparities through migration and local labour market adjustment take such a long time that relying exclusively on this adjustment mechanism may lead to underutilization of resources in depressed regions (Pissarides and McMaster 1990). Both migratory behaviour and migrant characteristics have an important influence on the convergence process (Greenwood 1975). 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 scale and productivity of the labour-exporting region, and benefit the labour-importing region. Furthermore, such migration can be persistent, and may not die away over time. For example, Williamson (1991) observed that, in the US, the real wage gap between urban and rural areas showed a striking persistence over five decades between 1890 and 1941, 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. Migrants with higher human capital endowments are expected to search for job opportunities over wider geographical areas and are clearly more mobile (McCann 2001). Migration can play

[2] In some countries β increases, in others the estimated parameter decreases.

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 scale effect of migration through the change in the ratio between skilled and unskilled workers (Etzo 2008). 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). Inflow of skilled labour can lead to an upward shift in productivity in the recipient regions. Although migration allows workers to maximize their individual utility, it may also increase regional disparities in income per capita at the aggregate level, depending on the skills of migrants (Fratesi and Riggi 2007).

Despite the earlier noted persistence of internal migration patterns, the volume and direction of migration may eventually change. Certain factors such as agglomeration externalities and relative wage dispersion effects are quite crucial to the impact of migration on receiving regions. Recent trends indicate a massive movement towards cities, not only from rural to urban, but also from smaller to larger cities. The theory of intervening opportunities suggests that opportunities matter more to migrants than distance (Stouffer 1940). Cities are places 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 (Glaeser 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, being geographically disadvantaged, are economically disadvantaged.[3] This highlights that economic geography, the attributes of migrants, their responsiveness to spatial disparities, regional economic adjustment processes and externalities associated with migration are all important, but complex, drivers of empirical estimates of the impact of net migration on growth and convergence.

In conclusion, the effect of migration on income growth and convergence remains an ongoing research issue. Past empirical studies appear to have led to contradictory results. The challenge is to identify the theoretical framework that is most strongly supported by the empirical findings. This is where meta-analysis can play an important role. Meta-analytic techniques provide a systematic analysis of the available empirical evidence from independently undertaken studies. Such techniques permit us to identify the relationships between the measured effects of migration and relevant study characteristics such as data source, scientific method, and the choice of geographical boundaries. We will therefore utilize meta-analysis in this paper as a method to compare the empirical findings quantitatively and to identify the causes for observed differences in the impact of net migration on economic growth.

3 A short introduction to meta-analysis: Analysis of analyses

3.1 Methodology

The research findings on a particular topic may indicate a great variety of conclusions and can be confusing and conflicting about central issues addressed by theory and practice. Meta-

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

analytical techniques can offer a clearer idea, compared with narrative literature reviews, of the variation in numerical outcomes across the literature and provide 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). Meta-analysis has clarified a controversial area of research in various cases (Stanley 2001). It is possible to combine the numerical findings from various studies by means of meta-analysis and to gauge the accuracy of the relationships even when the analysed sample suffers from publication bias through explicitly modelling the implication of such selection bias (see Nijkamp and Poot 2005, for an example).

In general, factual or methodological heterogeneity across studies, heteroscedasticity of effect sizes (which are the parameter estimates or statistical quantities of interest), and correlation of effect sizes between and within studies, can cause methodological problems when interpreting a meta-analysis.[4] Heterogeneity, defined as a variation of the mean among the effect sizes that are collected from primary studies, is a major concern in many comparative analyses. 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. While allowing for unexplained factors that drive some of the variation in effect sizes, the mean effect size should be clear and interpretable.

Heterogeneity in meta-analytical studies is handled in two main ways: first, by focusing on explaining the variation; and second, 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 analysis which explains the variation of effect sizes in terms of regressors that represent various study characteristics.[5] For the second approach, random and fixed effects models are used to predict population effect sizes on the basis of the sample of effect sizes collected from primary studies (e.g., Nelson and Kennedy 2009). The random effects model assumes that the underlying population parameter is itself drawn from a distribution. Hence, there are two sources of variation: within and between-study variance.[6] The fixed effects model assumes within-study variation only. Samples of effect sizes can of course be split into subsamples that on *a priori* or statistical grounds may be assumed to be homogeneous. In the fixed effects model, primary studies estimate a fixed population effect. For a fixed effects model, let T_j be the observed effect size of study j, $j = 1, \ldots, k$. It is assumed that $\delta_1 = \ldots = \delta_k = \delta$, where δ is the unobserved true common underlying effect. Therefore, a pooled estimate of δ is calculated in the fixed effects model as follows:

$$\bar{T} = \frac{\sum_{j=1}^{k} T_j / v_j}{\sum_{j=1}^{k} 1 / v_j} \tag{2}$$

in which v_j is the estimated variance of effect size T_j. The effect sizes are weighted by their estimated inverse variances, to account for differences in precision of the estimates, for example,

4 For a recent discussion on 'best practice' in meta-analysis in economics (with particular reference to environmental economics), see Nelson and Kennedy (2009).

5 Such descriptors are commonly study attributes that can be represented by categorical variables, which are then represented in a meta-regression analysis by binary dummy variables. Not all attributes are qualitative: the sample size of a primary study can be an important integer variable.

6 The common use of this approach refers to the cases where the source of variation cannot be identified (Sutton et al., 2000).

due to varying sample sizes.[7] The weighted average effect size $\bar{T}$ has an estimated variance $\bar{v}$, where:

$$\bar{v} = \frac{1}{\sum_{j=1}^{k} 1/v_j} \tag{3}$$

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 primary observation-level sampling error, known as within-study variance; and, second, there is the random variation of the effect sizes, known as between-study variance. Algebraically, the model is denoted as:

$$\begin{aligned} T_j &= \delta_j + \varepsilon_j \quad \varepsilon_j \sim N\left(0, \sigma_j^{\,2}\right) \\ \delta_j &= \delta + \mu_j \quad \mu_j \sim N\left(0, \tau_j^{\,2}\right) \end{aligned} \tag{4}$$

As in the fixed effects model, the estimated effect sizes are weighted by their inverse variances for the precise estimation of the mean effect size. However, in the random effects model there are two sources of variation and therefore the inverse weight of each effect size will be equal to $1/(v_j + w_j^2)$. In this case v_j represents the within-study variance, and w_j^2 denotes estimated between-study variance.[8]

The fixed and random effects weighted mean effect sizes may differ substantially if the studies are markedly heterogeneous (Egger et al. 1997a). Since the effect sizes are collected from various studies, a homogeneity test is usually run 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] The *Q*-statistic, 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:

$$Q = \sum_{j=1}^{k} \left[\left(T_j - \bar{T}_{.}\right)^2 \Big/ \left(v_j\right) \right] \tag{5}$$

"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). In meta-analyses in economics, the hypothesis of homogeneity is often rejected. We shall see in Section 4 that this is also the case for effect sizes that measure the impact of net migration on per capita income growth. In the presence of heterogeneity, meta-regression analysis is one way to account for heterogeneity systematically. This method will be applied in Section 5.

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[7] Ignoring this in calculations would overstate the importance of covariates in a meta-regression analysis (Thompson and Sharp 1999).

[8] For the estimation of between-study variance, see e.g., Shadish and Haddock (1994, p. 274).

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

[10] When the homogeneity hypothesis is not rejected, the meta-analyst usually adopts a fixed effects model because it is assumed that the estimated effect sizes only differ by sampling error. In contrast, when the hypothesis is rejected then a random effects model is applied. "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).

3.2 Meta-regression analysis

Meta-regression analysis is a statistical technique that integrates effect sizes gathered from various independent studies and explains the variation between 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 causes inherent heteroscedasticity in the meta-analysis sample, while the latter causes randomness of effect sizes. Moreover, using standard OLS estimation to explain the heterogeneity would lead to inefficient results, since effect sizes with a higher variance would get the same weight as effect sizes with a lower variance (Koetse et al. 2007).

Meta-analytical techniques have been developed to address these issues. 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, whereby the regression weights are inversely proportional to the precision of the estimates, and the estimation is conducted by weighted least squares (WLS). A linear fixed effects model is as follows:

$$T_j = \theta_0 + \theta_1 x_{j1} + \ldots + \theta_p x_{jp} + \varepsilon_j \quad \varepsilon_j \sim N\left(0, \sigma_j^{\,2}\right), \tag{6}$$

where T_j refers to the estimated effect size j, p denotes the number of moderator variables x_{jp}; and the θs are the coefficients to be estimated. In the fixed effects model, the weights are equal to the reciprocal of the sampling variances (weight for T_j is $1/v_j$), calculated by means of the usually reported standard errors or *t*-statistics of regression coefficients (Hedges 1994).[11] In standard statistical packages, the coefficients are correctly estimated with WLS, but the standard errors are calculated by means of a slightly different formula than in the fixed effect model, hence an adjustment is required.[12]

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). The mixed effects model allows for two variance components by assuming that the effects of between-study variables such as the type of data a study uses, are systematic (subject to sampling error), 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 (Lipsey and Wilson 2001):

$$T_j = \theta_0 + \theta_1 x_{j1} + \ldots + \theta_p x_{jp} + \varepsilon_j + \mu_j \quad \varepsilon_j \sim N\left(0, \sigma_j^{\,2}\right), \mu_j \sim N\left(0, \tau_j^{\,2}\right). \tag{7}$$

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. Our estimation is based on an iterative maximum likelihood estimator.

[11] The fixed effect estimates of Table 3 can be obtained by running a WLS regression of the effect sizes on a constant term only, with weights equal to the reciprocal of the sampling variances.

[12] The corrected standard error is generally obtained by dividing the reported standard error by the root mean squared error (RMSE) of the WLS regression. However, using so-called aweights in *Stata* (which interprets weights as replications) requires the reported RSME to be multiplied by $\sqrt{(N/k)}$ in which N is the sum of the weights and k is the number of effect sizes. Because Stata reports N in any case, the standard error of the fixed effects estimate can in fact with this software simply be obtained by calculating $1/\sqrt{N}$.

Each of the studies selected for meta-analysis will usually represent multiple effect sizes. Therefore, the studies with a high number of effect sizes may dominate the prediction of the overall mean effect size. A common procedure used to overcome this problem is to assign a within-study weight that is equal to the reciprocal of the number of observations obtained from the study (Nelson and Kennedy 2009). By using this approach we give equal weight to each study, though the impact of individual effect sizes varies.

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. 1997a). The empirical results of meta-regression analysis are given in Section 5.

4 Primary studies

4.1 Selection of primary studies and study characteristics

The primary studies in our meta-analysis all adopt the standard framework of the neoclassical model of growth and convergence, while most discussions on the effect of migration on income convergence follow the path-breaking research by Barro and Sala-i Martin (1992, 2004).[13] This paper will therefore address the impact of migration on income convergence as an empirical research issue. Equation (1) (or a linearization thereof) represents the regression equation that all the primary studies used in their analysis. There are two parameters of interest, β and γ, in Equation (1). First, we will focus on the effect of net migration on growth in per capita income, namely, 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. Jointly, this informs on whether the results of Barro and Sala-i-Martin (2004) are confirmed by other researchers.[14]

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, *Harzing's Publish or Perish* also reports the number of citations of each document that provide some measure of its impact. 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 1,200 articles were scanned.

However, many of these do not provide direct evidence of the impact of net internal migration on growth and convergence. One fundamental problem is the lack or limited reliability of internal migration data. Growth studies require long-term time series. Historical internal migration data are hard to obtain in many countries. Additionally, the time period of the data on migration flows often does not exactly match that of per capita income growth data. This makes it hard in empirical research to calculate the effect of migration for various periods, therefore, convergence studies tend to report relatively few regressions that include migration variables. Moreover, many of the studies that directly assess the effect of migration on income convergence have been fairly recent, with 60 per cent having been published after 2000.[15]

An additional problem that limits the number of comparable estimates in this study – and in economic research generally – is that innovation and uniqueness of empirical modelling is

[13] The foundation for all primary studies are the neoclassical closed economy models of Ramsey (1928), Solow (1956), Cass (1965) and Koopmans (1965). All predict that the per capita growth rate over a given period tends to be inversely related to the level of output or income per capita at the beginning of the period (Barro and Sala-i Martin 1992).

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

[15] Even excluding Barro and Sala-i-Martin (2004), whose estimates were originally published in 1995.

rewarded by referees and editors of journals, while replication is not encouraged (Hamermesh 2007). Meta-analysis requires the acquisition of a cluster of studies concerned with the same research question that use a common econometric specification, namely, a common metric of measurement. This significantly reduces the pool of empirical estimates that can be potentially suitable for summarizing by meta-analysis. In the present context, while the literature on convergence is huge, only papers that use, or build on, the migration-extended convergence model suggested by Barro and Sala-i Martin (1992, 2004) were selected. The selected studies for meta-analysis were all published after 1991.

The paper selection process initially yielded 17 studies with 94 observations. However, some serious comparability problems remained, and five papers had to be dropped. From the 12 remaining papers, 67 estimates of β and γ were obtained. Table 1 describes the sources of the estimates and some key features of these studies.[16]

A larger number of studies would have generated a larger set of observations on the statistical significance of the impact of net migration on growth, but in the present study the focus is on deriving estimates of the magnitude of the effect, which requires the regression models to be directly comparable (with at most corrections for differences in terms of the scale of variables or the effect of linearization). The trade-off is that greater comparability (and consequently greater homogeneity of the included estimates) reduces the size of the sample of estimates. However, it should be noted that the 67 available estimates cover nonetheless a diverse range of countries from different parts of the world.

The transformations that have been applied to some study findings concern the coefficients of initial income and of net migration. First, to ensure comparability of the net migration coefficients, such coefficients were converted, if necessary, to the equivalent coefficient for a variable that measures the ratio of annual net migration over total initial population. Second, if the coefficient of the initial income variable was given by linear regression estimation in a primary study, then the estimated coefficient was turned into its non-linearized equivalent according to $b = -[(1 - e^{-\beta T})/T]$ and, hence, $\beta = -\ln(1 + bT)/T$. In most of the papers, the dependent variable in the regressions was growth in personal income per capita, but in some cases (Chile, Norway, Sweden, Italy) the dependent variable referred to growth in gross regional product per capita. This had no impact on the meta-analysis.

4.2 Publication bias

Publication bias is a 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' suggests that insignificant results are more likely to be buried in a 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 (e.g., using a particular methodology) and the omission of studies not published in English.

[16] Several papers used the same analytical framework but did not generate estimates that corresponded with Equation (1) or its linearized equivalent, applied to the impact of net internal migration on interregional growth differentials. Examples are Gezici and Hewings (2004), Maza (2006) and Cashin and Loayza (1995).

Table 1. Primary studies used in the meta-analysis

No	Reference	Country	Number of estimates	Number of regions	T (typical length of time interval)	Observation period	Type of specification	Type of data in estimation	Control for endogeneity of net migration by instrumental variables
1	Barro and Sala-i-Martin (1992)	USA, Japan	3	48, 47	5	1955–87	non-linear	pooled	yes
2	Cardenas and Ponton (1995)	Colombia	3	24	39	1950–89	non-linear	cross-section	no
3	Persson (1997)	Sweden	8	24	10	1911–93	non-linear	pooled	no
4	Pekkala and Kangasharju (2001)	Finland	10	85	5	1975–95	non-linear	cross-section/pooled	yes
5	Shioji (2001)	Japan	12	39	30	1960–90	non-linear	cross-section	yes
6	Barro and Sala-i-Martin (2004)	USA, Japan, Germany, UK, Italy, France, Spain	14	on average 24	10	1920–90	non-linear	pooled	yes
7	Soto and Torche (2004)	Chile	1	13	5	1975–00	linear	pooled	no
8	Toya, Hosono and Makino (2004)	Philippines	2	13	5	1980–95	linear	pooled	no
9	Ostbye and Westerlund (2007)	Norway, Sweden	4	19, 24	5	1980–00	linear	pooled	yes
10	Etzo (2008)	Italy	6	20	1	1983–02	linear	pooled	no
11	Kırdar and Saraçoğlu (2008)	Turkey	2	67	5	1975–00	non-linear	pooled	yes
12	Peeters (2008)	Belgium	2	44	9	1991–00	non-linear	cross-section	no
Total number of observations			67						

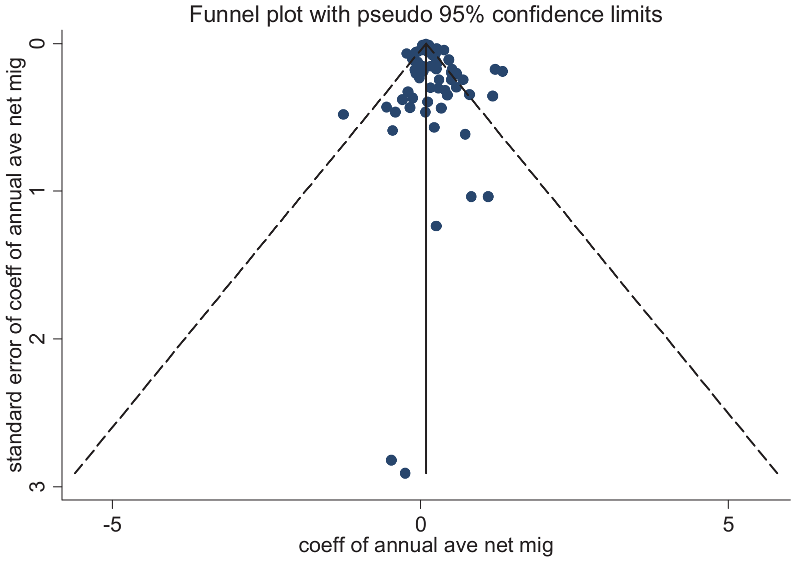

Fig. 1. Funnel plot for publication bias in reported estimates of net migration rates in growth regressions

There are various ways to reveal a possible bias. For instance, 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). However, such weighting can be rather subjective. Here we use a graphical method, the so-called funnel plot, which plots effect sizes against a measure of precision of the estimates. The funnel plot for the estimates of the coefficient of net migration rates is given in Figure 1. Along the vertical axis we measure the standard errors of the effect sizes down from 0, while the effect sizes themselves are measured along the horizontal axis. The vertical line represents the precision weighted average effect size, namely, the fixed effect estimate. The figure shows that the precision weighted average net migration coefficient is slightly positive. The broken lines represent the expected 95 per cent confidence intervals around this fixed effect for a given standard error, assuming no heterogeneity between studies. Besides easily revealing outliers, the plot is also indicative of publication bias when the scatter is strongly asymmetrical. This is not obvious in Figure 1.

However, publication bias is only one of the possibilities that may generate an asymmetric funnel plot (de Dominicis et al. 2008).[17] A formal statistical test of asymmetry of the funnel plot is known as Egger's linear regression test (Egger et al. 1997b). The regression equation may simply be denoted as follows: $t^* = \kappa + \lambda s^{-1}$, in which the t^* statistics of the estimates of the primary regression coefficient are regressed on the corresponding inverse standard errors, s^{-1}. The intercept measures the asymmetry. If the intercept is significantly different from zero, then this provides evidence for publication bias in the dataset (Sutton et al. 2000). In our case, the observations are distributed relatively symmetrically, albeit with a slight positive bias. This is confirmed by Egger's linear regression test which finds $\hat{\kappa} = 0.517$ with an associated p-value of 0.087, namely, not statistically significant at the 5 per cent level.

[17] There may be other biases (e.g. language bias, see Sutton et al. 2000, p. 109) that arise from the selection of primary studies and which we were not able to control for.

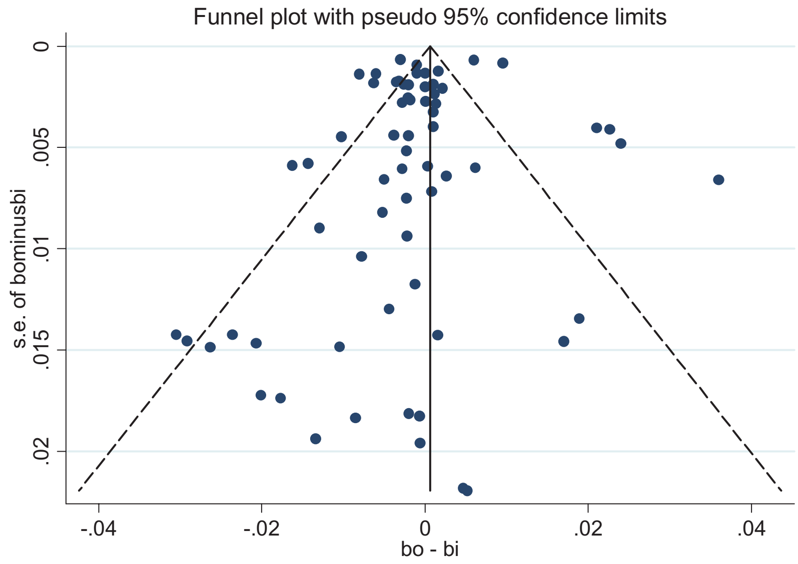

Fig. 2. Funnel plot for publication bias in reported estimates of the difference in beta convergence between including and excluding a net migration rate in growth regressions

Figure 2 shows the funnel plot for publication bias in reported estimates of the difference in beta convergence between including and excluding a net migration rate in growth regressions. Egger's linear regression test provides some interesting results concerning the beta coefficients of convergence. In regressions without the migration variable, there is no evidence of publication bias in the estimated beta, $\hat{\kappa} = -0.91$ with a p-value of 0.120. The corresponding estimate in the regressions with the migration variable is $\hat{\kappa} = 6.13$ with a p-value of less than 0.001. Hence, this could be a concern.[18] However, our primary focus is the pair-wise difference between the two estimated beta, for which we find that $\hat{\kappa} = -0.53$, with a p-value of 0.242. In this literature, a prior belief may have emerged through the seminal work of Barro and Sala-i-Martin (2004), who argued (using neoclassical theory) that the introduction of a net migration variable would lower the estimated beta. The Egger test suggests that there is no evidence of publication bias in the effect of the net migration variable on the estimated beta. Hence, we conclude that our sample of estimates obtained from the literature on the impact of net migration rates in growth regressions has not been affected by publication bias.

4.3 Descriptive statistics

Using the 67 effect sizes obtained from the studies listed in Table 1, the distribution of estimates of γ (coefficient of net migration) are within a range of −1.25 to 1.34, clustered around zero (see Table 2). The mean value is 0.18, with a standard deviation of 0.43.[19] Even without a formal test,

[18] However, one of the main research questions in studies that include a migration variable has been to assess how such a variable changes the rate of convergence. Meta-analytic inference on beta convergence itself can be obtained from a much larger range of studies (see Abreu et al. 2005 and Dobson et al. 2006). The sample of differences in beta coefficients we used for the meta-regression estimations does not suffer from publication bias.

[19] All estimations have been carried out in Stata 10.1. The meta-analysis estimation software is outlined in Sterne (2009).

Table 2. Descriptive statistics for the coefficient of net migration in growth regressions

Study characteristics		N	Mean	Std. Dev.	Min.	Max.
Level of development	developing country (*)	8	0.1819	0.7204	−1.2500	1.1000
	developed country	59	0.1798	0.3805	–0.5420	1.3410
Type of the data	cross-section (*)	21	0.2632	0.3297	–0.4060	0.7970
	pooled	46	0.1421	0.4630	−1.2500	1.3410
Type of the estimator	other estimators (*)	42	0.2253	0.3625	–0.4440	1.3410
	IV	25	0.1040	0.5170	−1.2500	1.1760
Time dummies	not accounted for (*)	58	0.1358	0.4004	−1.2500	1.3410
	accounted for	9	0.4653	0.5060	–0.4440	1.1760
Conditional variables	not used (*)	20	0.2004	0.4497	−1.2500	0.8350
	used	47	0.1717	0.4216	–0.5420	1.3410
Migration of highly skilled workers	not accounted for (*)	56	0.1574	0.4327	−1.2500	1.3410
	accounted for	11	0.2950	0.3949	–0.4060	0.7970
Total Sample		67	0.1800	0.4270	−1.2500	1.3410

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

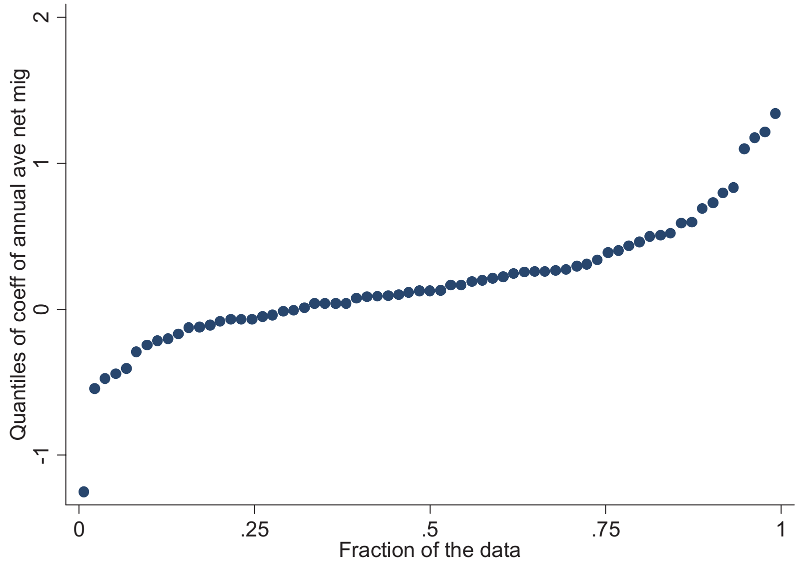

Fig. 3. Quantile plot of the distribution of the coefficients of net migration rates in growth regressions

this large standard deviation is indicative of considerable heterogeneity. Figure 3 shows the quantile plot of the estimated coefficients. Both the mean value and the median value (0.13) suggest a small positive impact of migration on the per capita income growth rate. However, the magnitude of the effect can only be meaningfully estimated when the precision of the estimates is taken into account by means of the fixed effects or random effects estimator, as will be discussed below. Here we simply note that only 2 of the 67 coefficients of net migration had a statistically significant negative value (at the 5% level), while 27 of the 67 estimates had a statistically significant positive value.

The Q-statistic of heterogeneity of effect sizes shown in Table 3 is 336.3, with 66 degrees of freedom. Hence, the null hypothesis of homogeneity is conclusively rejected with a p-value

Table 3. Fixed and random effects estimates

(a) The coefficient of the net migration rate in growth regressions

Method	Pooled estimate	95% CI LB	95% CI UB
Fixed	0.092	0.086	0.099
Random	0.133	0.099	0.168

Test for heterogeneity: Q = 336.27 with 66 degrees of freedom (p = 0.000).

(b) The beta convergence coefficient in regressions without a net migration rate

Method	Pooled estimate	95% CI LB	95% CI UB
Fixed	0.030	0.030	0.031
Random	0.027	0.025	0.030

Test for heterogeneity: Q = 714.24 with 66 degrees of freedom (p = 0.000).

(c) The beta convergence coefficient in regressions with a net migration rate

Method	Pooled estimate	95% CI LB	95% CI UB
Fixed	0.005	0.005	0.005
Random	0.029	0.025	0.034

Test for heterogeneity: Q = 5358.66 with 66 degrees of freedom (p = 0.000).

(d) The pairwise difference in beta convergence coefficients

Method	Pooled estimate	95% CI LB	95% CI UB
Fixed	0.0006	0.0001	0.0011
Random	–0.0003	–0.0021	0.0016

Test for heterogeneity: Q = 469.10 with 66 degrees of freedom (p = 0.000).

<0.001. I^2 (a measure of variation in the estimated gamma attributable to heterogeneity) is 80.4 per cent. 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 the present study, but may also provide additional insight into discussions in the recent literature on the effect of net migration on growth and on the convergence coefficient. We explain this variation by utilizing a set of moderator variables, in the form of binary dummy variables. These represent the characteristics of the primary studies.

The moderator variables, which are study features that may explain heterogeneity among the observed net migration coefficients, are presented in Table 2. Since the variables are in the form of binary dummies, reference categories must be selected for meta-regression analysis and these are shown by an asterisk (*). The statistical significance of the effect size variation, as well as the impact of each study feature on the net migration-rate coefficient, is investigated by means of multivariate analysis in Section 5. Descriptively, Table 2 suggests that the coefficient of net migration is smaller in regressions with pooled data than with cross-sectional data, with instrumental variable (IV) estimation, when time dummies are accounted for, and when covariates are used. However, the growth impact of net migration is greater when it refers to highly skilled workers only. The level of development of the country does not appear to have a noticeable influence on the coefficient of the net migration rate.

The second question of our study is whether the speed of convergence is influenced by including the net migration variable in the regression and, if so, to what extent? The interquartile

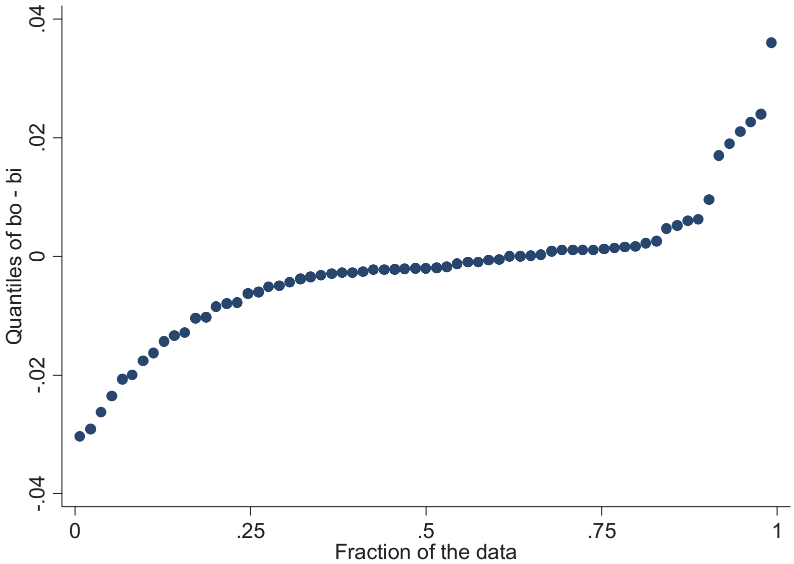

Fig. 4. Quantile plot of the difference in beta convergence in regressions without and with a net migration variable

range of values of beta convergence in the considered sample of regressions is from 0.02 to 0.04 (with 0.02 representing the commonly observed 'two per cent rule' in the literature; see Abreu et al. 2005).[20] Consistent with the positive effect of net migration on growth noted above, inclusion of migration in Equation (1) appears to increase the speed of income convergence slightly: the average β_o is 0.0302, whereas the average β_i is 0.0325. However, the proper comparison must be pair-wise, in which all other aspects of the regression specification remain the same. Figure 4 shows the distribution of the effect on beta convergence of including a net migration variable in the regression. The $\beta_o - \beta_i$ effect varies between −0.030 and 0.036, with the average being slightly negative (−0.002). This suggests that the migration variable in the economic growth regressions raises the beta convergence coefficient slightly, contrary to what Barro and Sala-i-Martin (2004) expected. However, a paired *t*-test indicates that the difference in means is only significant at the 10 per cent level (one-sided), $t = -1.59$. This result may be compared with the findings of Dobson et al. (2006) who ran meta-regressions of beta convergence coefficients and found that the inclusion of population, employment and labour force growth (variables which may be expected to have effects similar to net migration rates on beta convergence) in primary studies had mostly an insignificant effect on the speed of income convergence.

Table 3 reports the fixed and random effects estimates of (a) the coefficient of net migration in the growth regressions, (b) the coefficient of beta convergence without net migration, (c) the coefficient of beta convergence with net migration, and (d) the difference in beta coefficients. With weights determined by the precision of the estimates of the primary studies (as in Equation (2)), the fixed effects estimate of the coefficient of net migration is 0.092. The random effects estimate, which is always closer to the unweighted mean (0.18, see Table 2) is 0.133. Clearly these results suggest that the effect of the net migration rate on growth ranges between 0.092 and 0.133. In rounded terms we conclude that the average estimated effect of a one

[20] Beta coefficients of growth regressions without a net migration rate were not reported in the published primary study by Shioji (2001). These estimates were kindly provided for the meta-analysis by the author.

percentage point net migration rate on the per capita income growth rate is about 0.1 percentage points.

Table 3(b) shows that when growth regressions are run without a net migration variable in the specification, the fixed effects estimate of beta convergence in our sample is 0.030. This is larger than the celebrated 2 per cent rule, but Dobson et al. (2006) note in their meta-analysis that the mean rate of convergence derived from intra-national studies is considerably larger than the rate obtained from cross-national studies and their meta-sample average (unweighted) of 0.025 for intra-national studies is consistent with our evidence. In our sample of 67 estimates, the fixed effects estimate of beta convergence drops considerably (to 0.005), when the net migration variable is introduced in the growth regression. However, there is huge heterogeneity among these estimates and the random effects estimate is therefore more useful. The random effects estimate suggests that introducing a net migration variable into the growth regression increases beta slightly (from 0.027 to 0.029).

This small positive effect is confirmed by formally calculating a fixed and random effects estimate of the difference. The fixed effects estimate is 0.0006 (see Table 3(d)), but the random effects estimate has a 95 per cent confidence interval running from –0.002 to 0.002, with the point estimate being negative, albeit only in the fourth digit after the decimal point (the precision-weighted mean is –0.0003). Given the considerable heterogeneity, the random effects estimate is more informative in the present context because it spreads the precision weights (derived from the reciprocals of the squares of the observed standard errors) more evenly than the fixed effect estimate (Borenstein et al. 2009). We conclude that including a net migration variable in an intra-country growth regression raises the speed of beta convergence slightly.

Theoretically, if a variable that is correlated with the included variables is excluded from the model, the predicted parameters are biased (Verbeek 2004). Therefore, unless $\gamma = 0$, the deletion of the net migration rate variable from Equation (1) would lead to biased estimates of other parameters, including the estimated beta. If $\gamma = 0$, the expected value of β_o equals the expected value of β_i (including an irrelevant variable leaves the estimate unbiased although the precision is reduced). Figure 5 presents the bias caused by deletion of the net migration rate variable on the difference in estimated beta convergence coefficients without and with the net migration rate. The northwest quadrant represents the neoclassical convergence combination of a negative estimate of γ, combined with a positive bias. The southeast quadrant represents the endogenous growth combination of a positive γ together with a negative bias. The precision-weighted averages of γ and $\beta_o - \beta_i$ are in the southeast quadrant. Given the heterogeneity, the relationship between estimated γ and $\beta_o - \beta_i$ is not precise ($R^2 = 0.07$) but statistically significant at the 5 per cent level.

5 Meta-regression analysis

In meta-regression analysis we can assess whether study characteristics jointly affect the mean effect size in a statistically significant way. Since we have a modest number of observations, we aim to formulate a parsimonious model that brings further insights to methodological and empirical discussions. The reported regressions have been selected on grounds of theoretical considerations and goodness of fit.

5.1 Meta-regression analysis of the coefficient of net migration

Table 2 shows that the mean estimate of the migration coefficient varies across a number of study characteristics: type of data, type of estimator, etc. We report our results by using three

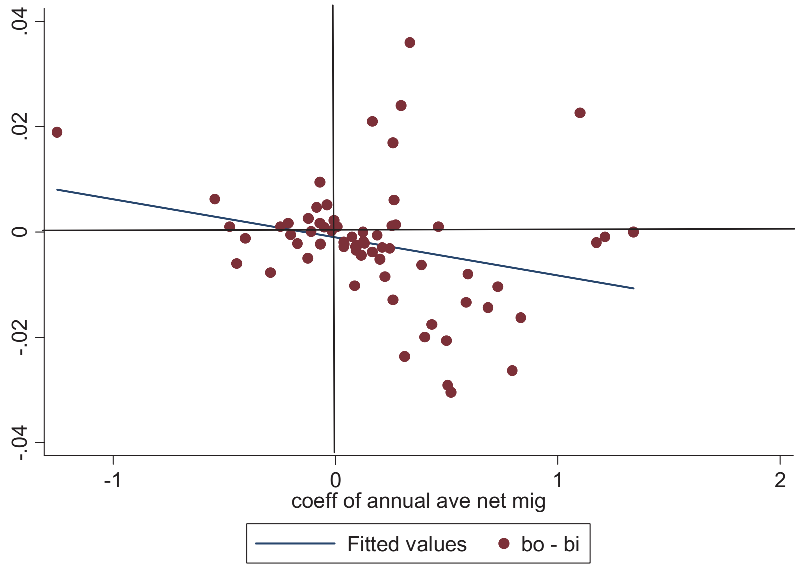

Fig. 5. Scatter plot (and least squares regression line) of coefficients of the net migration rate and the corresponding difference in beta convergence in regressions without and with a net migration variable

estimation techniques that were discussed in Section 3.2. These are the WLS, fixed effects and mixed effects models. The results are given in Table 4. Varying the estimators allows us to identify the robustness of the results. The results are in fact qualitatively highly consistent across the three approaches. Nonetheless, it is not realistic to expect meta-analysis to explain the entire variation that exists in the data (Nelson and Kennedy 2009). The outcome of empirical testing cannot be predicted beforehand, precisely because the sources of influence on the outcome are both numerous and sometimes unidentifiable (Raudenbush 1994).

Heterogeneity and quality variation of data are important issues that affect empirical estimates and therefore meta-analysis. In general, there is a consensus that regional scale data are more homogenous compared with cross-country data (Barro and Sala-i Martin 1992; Abreu et al. 2005). However, in countries within which regional disparities are very high or the data of lesser quality, estimates may be affected by this. Additionally, the level of development may have an impact on the role of migration in growth regressions. For instance, in developing countries migration would be more homogeneous than in developed countries. The migration that takes place in the developing world is predominantly rural to urban, while migrants of the developed world have a tendency to move between cities within and between countries in the same part of the world. This contributes to agglomeration and its positive impact on growth (World Bank 2008). Table 4 shows that the dummy variable for development has a positive coefficient in the meta-regression models, but the coefficient is not statistically significant.

There are two important econometric issues in the migration and growth literature: simultaneity bias, and omitted variable bias (OVB) (Kırdar and Saraçoğlu 2008). Areas with higher than average real wage growth are expected to exhibit relatively strong net in-migration flows. There is therefore a two-way causality between growth and migration. For this reason, OLS may generate biased estimates. Thus, the use of two stage models such as 2SLS and IV is highly recommended in the literature. Table 4 suggests that IV estimation leads to a reduction in the

Table 4. Meta-regression analysis of the coefficient of net migration in growth regressions

Study characteristics		WLS[a]	Fixed effects[b]	Mixed effects
Development	developed	0.1874	0.0680	0.1845
		(0.1350)	(0.1100)	(0.1732)
	developing (†)	–	–	–
Type of the data	pooled	–0.3146***	–0.1640**	–0.2310**
		(0.1167)	(0.0740)	(0.1044)
	cross-section (†)	–	–	–
Type of the estimator	IV	–0.3868***	–0.0793	–0.1069
		(0.1260)	(0.0760)	(0.1038)
	others (†)	–	–	–
Time dummies	accounted for	0.4432***	0.3636*	0.3381**
		(0.1352)	(0.1874)	(0.1674)
	not accounted for (†)	–	–	–
Covariates	used	0.0196	0.0561**	0.0105
		(0.1174)	(0.0210)	(0.0996)
	not used (†)	–	–	–
Migration of highly skilled workers	accounted for	0.2857	0.1691	0.1124
		(0.1748)	(0.1036)	(0.1303)
	not accounted for (†)	–	–	–
Constant		0.1832	0.1387	0.1580
		(0.1271)	(0.1208)	(0.1535)
N		67	67	67
Adj. R^2		0.2395	0.1550	0.1010

Notes: (†) refers to the reference categories in the regression analysis. The dependent variable is the coefficient of the average annual net migration rate in growth regressions. Standard errors are given in parenthesis. *, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.

[a] WLS: an equal weight of '1' is assigned to each study in the database, with the weight of individual estimates within a study being given a weight equal to the reciprocal of the number of estimates obtained from the study.

[b] Fixed effects: observations are weighted by the inverse squared standard error of the effect sizes. Mixed effects: see the main text. The adjusted R^2 in the mixed effects model refers to the proportion of between-primary regression variance explained.

positive effect of migration on real income growth. However, this effect is statistically significant only in WLS estimation.

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, a panel data methodology controls for time-invariant structural differences across the regions (Cashin and Loayza 1995; Etzo 2008). Table 4 shows that using pooled data decreases the effect of migration on growth, and this is the case for all meta-regression estimators (significant at the 5% percent level).

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 (Shioji 2001; Etzo 2008). Highly-skilled migrants are expected to have a stronger positive impact on growth than lesser-skilled migrants. They are also more mobile. Researchers are increasingly questioning the measurement of migrants' skills, and are 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.[21] In our meta-sample, only studies on Italy and Japan have considered highly skilled migrants as an explanatory variable. We accounted for the composition effect with a migrant-skill dummy, which turned out to be positive in all three models, but which was statistically insignificant.

Various covariates are included in growth regressions to avoid omitted variable bias. Sectoral composition and per capita public investment are among the most frequently used covariates. 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 (see Cardenas and Ponton, 1995). The effect of the inclusion of such covariates appears to have a positive effect on the estimated coefficient of net migration, but the effect is only statistically significant in the case of the fixed effects model.[22]

In measuring the consequences of migration, it is important to allow for exogenous shifts and 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 may otherwise be biased. We find a positive, and statistically significant, effect of between 0.3 and 0.4 for studies that allowed for time dummies.

5.2 Meta-regression analysis on the difference in beta coefficients with and without migration

Table 5 reports the results of meta-regression analysis of the impact of a net migration variable in growth regressions on the estimated coefficient of beta convergence. The estimators that are compared are the same ones as in Table 4. The dependent variable is the coefficient of beta convergence in growth regressions without a net migration covariate minus the corresponding coefficient of beta convergence when a net migration covariate has been included. If a study characteristic makes this difference more positive, it leads to greater support for the neoclassical model, whereas if the study characteristic makes the difference more negative, it tends to be more supportive of net migration reinforcing economic growth (see again Figure 5). The reported models have been selected on grounds of relative goodness of fit or *a priori* plausibility of the results.

The time span of the data used in the estimations in primary studies is an important variable in convergence analysis. Beta convergence is a long-run process that can only be estimated with data over a long time span, to avoid business cycles biasing the estimate. The bias introduced by omitting a net migration variable in the regression may also be affected by the time span of the data. Table 5 shows that a longer time frame is needed to capture the neoclassical growth process: the time interval dummy has a statistically significant positive coefficient, but only in the fixed effects model.

Although we did not find publication bias among the selected studies (see Section 4.2 above), there is a possibility that studies published in journal articles find on average a different effect from non-refereed working papers. Table 5 shows that this is indeed the case. Published

[21] The human capital embodied in a migrant worker with a low educational attainment, but with a high level of work experience, is likely to be underestimated when only education is taken into account. Common data deficiencies are a major obstruction to further analysis along these lines.

[22] We included many other controls such as regional fixed effects, heteroscedasticity (if accounted for in primary studies) and type of publication in our estimation. The reported results in Table 4 are robust to the inclusion of these variables. They turned insignificant in all estimations, except type of publication is negative and significant only in mixed effects estimation at 10 per cent level.

Table 5. Meta-regression analysis of the difference in beta convergence between growth models with net migration and without

Study characteristics		WLS[a]	Fixed effects[b]	Mixed effects
Typical length of time interval	10 years or more	–0.0022	0.0049**	–0.0023
		(0.0030)	(0.0024)	(0.0026)
	less than 10 years (†)	–	–	–
Type of publication	published	0.0092**	0.0133***	0.0103***
		(0.0035)	(0.0040)	(0.0036)
	Working paper (†)	–	–	–
Regional fixed effects	accounted for	0.0118***	0.0110***	0.0103***
		(0.0035)	(0.0039)	(0.0035)
	not accounted for (†)	–	–	–
Covariates	used	–0.0064**	–0.0082**	–0.0057*
		(0.0031)	(0.0041)	(0.0034)
	not used (†)	–	–	–
Instrumental variables	used	0.0089***	0.0019	0.0041*
		(0.0029)	(0.0017)	(0.0022)
	not used (†)	–	–	–
Migration of highly skilled workers	accounted for	–0.0137***	–0.0144**	–0.0136***
		(0.0043)	(0.0062)	(0.0037)
	not accounted for (†)	–	–	–
Constant		–0.0085**	–0.0090***	–0.0055
		(0.0036)	(0.0027)	(0.0037)
N		67	67	67
Adj. R^2		0.2751	0.2598	0.3793

Notes: (†) refers to the reference categories in the regression analysis. The dependent variable is the coefficient of beta convergence in growth regressions without a net migration covariate minus the corresponding coefficient of beta convergence when a net migration covariate has been included. Standard errors are given in parenthesis. *, **, *** indicates significance at the 10%, 5% level, 1% levels respectively.

[a] WLS: an equal weight of '1' is assigned to each study in the database, with the weight of individual estimates within a study being given a weight equal to the reciprocal of the number of estimates obtained from the study.

[b] Fixed effects: observations are weighted by the inverse squared standard error of the effect sizes. Mixed effects: see the main text. The adjusted R^2 in the mixed effects model refers to the proportion of between-primary regression variance explained.

studies report more positive values for the difference in estimated betas, suggesting that the non-orthodox interpretation is more common among the working papers.

The primary studies included in the meta-sample refer to regions across a wide array of countries. Regional fixed effects may capture the unobserved heterogeneity of various socio-economic differences between the regions. The speed of convergence increases if we allow for higher level of regional variation (Kırdar and Saraçoğlu 2008). Including regional fixed effects provides arguably better specified growth regressions and shifts the difference in beta coefficients upwards. The results suggest indeed that introducing a net migration variable in the growth model has an impact on beta that is about one percentage point more positive when regional fixed effects are used than when they are not. The effect is highly significant in all three models.

The inclusion of additional covariates in growth regressions controls for the possibility of spatial differences in steady state growth path, and bias in estimates of beta convergence (Abreu et al. 2005). Once such variables are included, the impact of the net migration variable on the difference in betas becomes more negative.

As noted previously, the endogeneity of net migration in growth regressions (migrants are disproportionally attracted to the fastest growing regions, leading to a high correlation between net migration and growth) can be accounted for by means of the instrumental variables technique (Barro and Sala-i Martin 2004). Table 5 confirms that using an instrument makes the difference between betas with and without a migration variable slightly more positive. However, the coefficient is statistically insignificant in the fixed effects model.

As in Table 4, we also examine again the effect of the measured skill level of migrants on the growth regression. We have seen that the introduction of the net migration variable on average increases the role of initial income (i.e., beta convergence) in explaining growth, and if the net migration variable refers to highly skilled migrants only, the (negative) difference between the estimated speed of convergence with and without the migration variable appears to become even greater, and the effect is statistically significant across all three estimators. This is consistent with the migration of highly skilled workers reinforcing an increasing returns growth process.

Finally, the results reported in Tables 4 and 5 did not exploit the fact that corresponding observations in the two meta-regression analyses came from the same primary regression. The error terms of the model for the net migration rate may therefore be correlated with the error terms of the model for the differences in betas and these correlations can be exploited by means of the seemingly unrelated regression (SUR) model estimator (e.g., Zellner 1962). The SUR approach was applied to the WLS model of Tables 4 and 5. However, the results were very similar to those already discussed. To save space they are not included.[23]

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 growth and convergence by applying several meta-analytical techniques which provided a quantitative methodological description for, and measure of, effect size heterogeneity that exists across the primary papers. The results appear rather consistent across techniques. However, data problems – particularly regarding the measurement of growth in regional income per capita and interregional migration over long time intervals – have been a common difficulty for researchers. This has limited the number of directly comparable estimates.

As a result of synthesizing the empirical work, we conclude that the overall effect of net migration on growth in real income per capita is positive, but small. A one percentage point increase in the net migration rate (equivalent to a one percentage point increase in the rate of population growth) increases the rate of growth in per capita income by about 0.1 percentage points. In contrast, in a standard neoclassical framework of a constant returns to scale economy with a composite good being produced and labour's share of income being 70 per cent, an increase in the growth in labour supply of 1 percentage point would decrease growth in per capita income by 0.3 percentage points. However, with perfect capital mobility this effect would be offset by a commensurate increase in the capital stock (of 1 percentage point) and growth in real per capita income would remain unchanged. A positive sign of a net inward migration coefficient in a real income growth regression is consistent with the perspective of the new endogenous growth theories and the new economic geography (which emphasize the strengthening benefits of agglomeration) rather than with the neoclassical model with homogenous labour. This conclusion reinforces recent evidence in favour of the new economic geography by Fingleton and Fischer (2010).

[23] The SUR estimates are available from the authors upon request.

Moreover, we find that the estimated rate of beta convergence (the rate at which the economy converges to its steady state growth path) is also on average increased somewhat by introducing net inward migration in the growth regression. Without net migration, estimated beta (conditional) convergence is around 2.7 per cent per annum across our sample of studies of internal migration and growth. The inclusion of a net migration variable increases this to about 2.73 per cent.[24]

Furthermore, our results suggest that the nature of the data (pooled data versus cross-section; the length of the time interval) has a significant influence on the impact of the migration variable in growth regressions. The results also highlight the importance of two-stage estimation techniques such as IV estimation to overcome the two-way causality problem in the relationship between migration and growth. The IV method reveals a lower migration effect on income growth. We also identify the importance of controlling for unobserved regional heterogeneity by means of fixed effects estimation. Finally, the estimates of the impact of net migration on per capita income growth depend on the model specification, in terms of the selected covariates, including the use of time dummies.

The nature of the mechanisms through which net migration increases real income growth still has to be explored in further primary research. The impact of migration on capital accumulation and technological change would be central issues in this context. The composition of the migration flows in terms of the age, skills and diversity of the migrants may play an important role too. Finally, the present paper has focused only on internal migration, but the impact of migration on income growth and convergence is clearly also an important topic in the current debate on the desirability and sustainability of current immigration levels in developed countries. Further primary research, and subsequently some synthesis by means of meta-analysis, may be expected in that context as well.

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[24] Based on Table 3, panels (b) and (d) respectively.

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El efecto de la migración en el crecimiento de ingresos y la convergencia: pruebas metaanalíticas

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Resumen. Comparamos un conjunto de estudios econométricos que miden el efecto de la migración interna neta en modelos neoclásicos de convergencia de ingresos reales a largo plazo y de ahí obtenemos 67 tamaños de efectos comparables. La estimación ponderada por precisión de la beta-convergencia es aproximadamente del 2.7 por ciento. Un aumento de un punto porcentual en la tasa de migración neta de una región aumenta la tasa de crecimiento de ingresos per cápita en dicha región en un promedio de aproximadamente 0.1 puntos porcentuales. El introducir una variable de migración neta en una regresión de crecimiento aumenta ligeramente el valor estimado de beta-convergencia. Los estudios que usan modelos de panel o métodos de estimación por VI producen coeficientes menores de migración neta en regresiones de crecimiento, mientras que sucede lo contrario para regresiones que controlan migración altamente cualificada.

JEL classification: O15, O18, R23, R11

Palabras clave: Migración interna, crecimiento económico, convergencia, metaanálisis, modelo neoclásico, disparidades regionales

要約　長期的に実質所得が収束する新古典派モデルにより国内移住の実質的効果を計測した計量経済学的研究事例を比較すると同時に、67の同等の効果規模を導出する。ベータ収束のプリシジョン加重推計値は約2.7%である。一地域の純移住率1パーセントポイントの上昇は同地域の一人当たり所得を約0.1パーセントポイント増加させる。 成長回帰分析に純移住変数を導入するとベータ収束の推計値がやや大きくなる。パネルモデルまたはIV推計法を使用した研究では成長回帰分析の純移住変数の係数が小さくなるが、熟練労働者の移住をコントロールすると結果が逆になる。