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Why Do Rates of Convergence Differ? A Meta-Regression Analysis

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Abstract

There have been many tests of the convergence hypothesis yielding many different estimates of b (the speed of convergence). Narrative reviews of the convergence literature hint at possible reasons for the study-to-study variation in the value of b, but such reviews are selective and informal. In contrast, meta-regression analysis provides a more formal and objective review of the literature. It is shown that study design and methodology are important determinants of the reported convergence rate, especially in cross-national studies. There is also evidence of general misspecification in the literature.

Keywords: b-convergence; convergence hypothesis; meta-regression analysis; neo-classical growth theory

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1. Introduction

The question as to whether the per capita incomes of rich and poor countries are converging over time has been the subject of much empirical scrutiny in recent years although the notion of convergence has its origins in the neoclassical growth model of the 1950s (Solow, 1956). According to neoclassical theory if different countries are at different points relative to their balanced growth paths, and if structural differences between countries are accounted for, poorer countries should grow faster than richer ones. A key characteristic of the convergence literature is the reporting of a rate of convergence, which following Barro and Sala-i-Martin (1991) is commonly known as β-convergence. However, after a perusal of the literature the interested researcher is likely to be struck by the wide variety of estimates and left wondering as to the 'true' rate of convergence.

In early convergence studies the value of β was found to be close to 0.02, suggesting that convergence across countries is taking place at an average rate of two per cent per year (Barro, 1991; Barro and Sala-i-Martin, 1995; Mankiw et al, 1992; Sala-i-Martin, 1996). With the availability of a larger variety of data sets and estimation techniques in more recent years, estimates of β have become substantially more varied. The role played by differences in study design and methodology in influencing the reported rate of convergence has been hinted at in a number of narrative reviews of the growth and convergence literature (de la Fuente, 1997; Rassekh, 1998; Temple, 1999). For example, de la Fuente (1997, p.68) comments "…the available estimates of the … convergence parameter(s) appear to be quite sensitive to sample selection, econometric specification, and even to the list of regressors included in the equation". While these reviews are insightful in their own right, they tend to be selective in their coverage of the β-convergence literature, due in part to the natural space limitations of discursive reviews, and can only offer informal evidence as to the reasons for variation in reported convergence rates. To date no study has attempted to formally measure the effect of differences in study design and methods on the estimated value of β.

Formally investigating the roles played by sample design and methodology in determining β can be usefully achieved via meta-analysis, a statistical approach that allows one to quantitatively evaluate variation in empirical research results. Arguably, if there are numerous independent studies of a particular subject area where data sets and methods differ, then combining their results can provide more explanatory power than simply listing and discursively analyzing individual results (Stanley, 2001). In economics meta-analysis is usually applied in the form of a meta-regression analysis (MRA), where in a simple regression the dependent variable becomes the summary statistic (or regression parameter) of interest drawn from each study and the researcher creates a set of explanatory variables describing differences (or similarities) in the design of the studies under scrutiny (Stanley and Jarrell, 1989).[4] In this paper this technique is applied to a compilation of the empirical estimates of β reported specifically in the literature on convergence in order to investigate the role played by aspects of study design in the large variety of estimates of β.

The paper is structured as follows. Section 2 examines the concept of β-convergence and describes how β is estimated in the literature. In section 3 the nature of the MRA is described and the choice of the explanatory variables is discussed. Section 4 presents the results and section 5 concludes.

2. The Concept of β-Convergence

According to neo-classical theory the driving force behind convergence is the assumed diminishing returns to capital. The low ratio of capital to labor in poor countries makes the marginal product of capital high thus promoting faster growth than in countries with a high capital to labor ratio. If the only difference across countries is initial levels of capital, poorer countries will grow faster than richer ones and there is a convergence to the same steady state. This is known as unconditional β-convergence. Where there are structural differences across countries there will be conditional β-convergence: countries converge to different steady states but at a common speed.

In studies using cross section data the convention is to measure convergence in the way suggested by Barro and Sala-i-Martin (1991, 1995). The convergence measure can be related to the transitional growth process in a neo-classical model. Accordingly, the transition process of output or income per capita in country i at time t (y_{it}) and over the period T, can be approximated as:

$$(1/T) \times \log(y_{it}/y_{i,t-T}) = x_i^* + \log(y_i^*/y_{i,t-T})(1 - e^{-\beta T}) \times (1/T) + u_{it} \tag{1}$$

[4] Examples of MRA in economics include Button and Kerr (1996), Card and Krueger (1995), Görg and Strobl (2001), Jarrell and Stanley (1990), Phillips (1994) and Stanley (1998).

where x_i* is the steady state per capita growth rate, y_{it} is output per effective worker, y_i* is the steady state level of output per effective worker, β is the coefficient of the rate of convergence, and u_{it} is a disturbance term. The term β measures the speed at which y_{it} approaches y_i*.

To allow for structural differences between countries conditioning variables (not shown) can be included when estimating the following non-linear equation:

$$(1/T) \times \log(y_{it}/y_{i,t-T}) = a - (1 - e^{-\beta T})(1/T) \times \log(y_{i,t-T}) + u_{it} \qquad (2)$$

If conditioning variables are included in (2) and β is positive, there is conditional convergence: in the long run each country is converging towards its own steady state level of income at a common speed given by β. On the other hand, if (2) is estimated without conditioning variables a positive β coefficient measures the rate of unconditional convergence: the speed at which countries are approaching a common steady state income level.

Some convergence studies obtain the rate of convergence indirectly by estimating a linear equation:

$$(1/T)\log(y_{it}/y_{i,t-T}) = \mathrm{a} - b\log(y_{i,t-T}) + \varepsilon_{it} \qquad (3)$$

where $a = x_i^* + \log(Y_i^*)[(1 - e^{-\beta T})/T]$ and $b=(1 - e^{-\beta T})(1/T)$ in (1). The coefficient measuring unconditional convergence is derived from the b term while the conditional convergence coefficient is obtained in a similar manner following inclusion of conditioning variables. A negative and significant b coefficient in (3) is interpreted as evidence of β-convergence.

The concept of β-convergence has been criticized extensively in recent years. One line of attack focuses on the test for β-convergence, which involves estimating a cross section (OLS) regression. Typically, researchers have estimated β for the sample period as a whole and for individual sub periods (usually five or ten year intervals) within the overall period. But cross sectional estimation is problematic because not all of the relevant conditioning variables will be included in a cross section regression. For example, it is well known that there are persistent differences in the level of technology and the nature of institutions across countries yet these are ignored in cross section models (Islam, 1995). If relevant variables are omitted there will be a non-zero covariance between the error term and the β coefficient, rendering the estimate of the convergence parameter biased and inconsistent.

One solution to this problem is to pool the data and use panel estimation methods. The simplest of the panel methods includes a set of dummies to account for unobserved time invariant differences for each cross-sectional unit, also known as the least squares dummy variable (LSDV) approach. One of the drawbacks with the LSDV approach, however, is the potentially large loss of degrees of freedom depending on the number of cross-sectional units. A number of other panel data estimators are also available including the fixed effects estimator (FE), the random effects estimator (RE) and the generalized method of moments estimator (GMM) for dynamic models, and their use has become increasingly common in β-convergence work. The researcher can also choose between FE and RE models by using a specification test (Hausman, 1978) although a degree of caution needs to be exercised in deciding between these alternatives as "…there is no simple rule to help the research navigate past the Scylla of fixed effects and the Charybdis of measurement error and dynamic selection. Although they are an improvement over cross section data, panel data do not provide a cure-all for all of an econometrician's problems" (Johnson and DiNardo, 1997, p.403).

Another issue concerns one of the fundamental assumptions of the classical approach to convergence, that steady state growth rates are homogeneous (countries converge to different levels of per capita income but at the same speed). According to Lee *et al* (1997) the homogeneity assumption poses a serious problem because it can lead to biased estimates of the speed of convergence. This is also true when the data is pooled and estimation is done with panel methods (such as fixed effects). Lee *et al* say the problem can be overcome by developing a stochastic model of growth that formalizes the notion of heterogeneity: countries may converge to different levels of per capita income at different speeds. In their time series analysis, both trend stationary and difference stationary models strongly reject the restriction of a common technology growth rate across a large sample of countries. Lee et al's results show that cross-sectional and panel estimates will not reveal rapid convergence from some initial output levels even when it is present.

While the time series approach to convergence (including panel unit root tests) has made an important contribution to the literature it is not possible to include results from time series studies in the MRA because they do not derive a rate of convergence comparable to that derived in cross section and panel studies, as would be required in MRA (see, Stanley, 2001).[5] Furthermore, although times series work has undermined the traditional approach to convergence (see, for example, Evans and Karras, 1996), estimating β (either via OLS or panel methods) continues to be popular with researchers as evidenced by the large number of studies in the sample that date from more recent years.

3. Meta-Analysis and Description of Sample

In order to explain variation in the estimated parameter of interest due to differences in sample design across studies Stanley and Jarrell (1989) suggest estimating an equation as follows:

$$Y_j = \beta_0 + \sum_{k=1}^{K} \beta_k Z_{jk} + e_j \qquad j=1, 2, 3\ldots..N \qquad (4)$$

where Y_j is the estimate of the reported variable of study j from a total of N studies and Z_{jk} are meta-independent variables which proxy characteristics of the empirical studies in the sample so as to explain the variation in Y_j across studies. It is with this in mind that we created our sample of convergence rate estimates and generated a set of explanatory variables that potentially vary across these.

[5] Another approach, not included in the MRA, measures the cross-sectional dispersion of per capita income, known as σ-convergence. If the standard deviation is decreasing over time there is evidence of σ-convergence. Equation (2) can be used to show that the cross-sectional dispersion in income does not necessarily decrease over time even with β-convergence because there are random shocks. Therefore, β-convergence is a necessary but not a sufficient condition for σ-convergence (Quah, 1993).

The data set for the empirical analysis comprises 56 papers (published and unpublished) where the principal topic of investigation is testing the convergence hypothesis. The principal sources used in compiling the data set were Bath Information and Data Services, Institute for Scientific Information and Ingenta. International Monetary Fund and World Bank publications lists were also consulted along with lists from research groups such as National Bureau of Economic Research, Center for International Development and Center for Economic Policy Research. The catalogues of the libraries at the Economic Commission for Latin America and the Caribbean and the Commonwealth Secretariat were also used, as was the Journal of Economic Literature. The literature search produced more than 56 studies but as noted above it proved necessary to omit time series studies and restrict the analysis to those studies (OLS and panel) that are directly comparable in that they use cross section data to estimate β and associated standard errors.

The empirical studies of β-convergence can be grouped into three categories: (1) cross-national: the defining geographical unit is the country as a whole, (2) intra-national: regions within a country are considered, and (3) ultra-national: regions that reach beyond national boundaries (such as regions of the European Union) are considered as the geographical unit. For the purpose here, the sample is divided into cross-national and intra-national studies of convergence, with (3) included with the studies in (1) given their small numbers and separate analyses are conducted on these two groups. Lists of studies for the cross-national and intra-national groups are given in Tables 1 and 2, respectively.

Since most papers are at least in part specifically concerned with examining the robustness of their results over different specifications, sample periods, data sources and estimation techniques, they almost all contain several estimates of β. Given that our specific concern is with potential differences in estimates across these features and in order to avoid arbitrarily picking single estimates from multi-estimate studies, we have, where available, included several estimates from each study, as long as differences between these can be described by the explanatory variables.[6] As can be seen from Tables 1 and 2, the number of estimates from individual studies included range widely. Stanley (2001) notes that including more than one estimate from a single study may be problematic if these give papers a disproportionate importance. Clearly, given the large number of different studies from which our estimates are taken and the number of papers from which there are numerous estimates, this is not the case here.

Our first concern is to derive the appropriate dependent variable, i.e., Y_j in (4). In his review of the use of meta-analysis in economics Stanley (2001) emphasizes the importance of being able to compile a comparable summary statistic of the variable of interest. In our case this is straightforward since the estimated rate of convergence (β) measures the rate at which a country is converging to its steady state level of income. The smaller is β the longer it will take for a country to reach steady state, while the larger β is the quicker the transition to steady state. Since the convergence rate measures the time taken for countries/regions to converge to their steady state the interpretation of β is straightforward.

[6] In cases where this was not possible we arbitrarily chose one estimate from the homogenous group (according to our set of explanatory variables). Also, we excluded the observations of all those that we could not group according to any of our explanatory variables.

The rate of convergence may be estimated indirectly (as in (3)) or derived directly from a non-linear specification as in (2). Therefore, a simple zero-one type dummy variable, NL, is created that takes the value of one when non-linear estimation is used and zero otherwise, to be included in (4) as an explanatory variable in order to determine whether the use of these two types of specifications has any implications for the rate of convergence.

As noted above, it is conventional to distinguish between estimates of unconditional and conditional convergence, where in the former the only explanatory variable is the initial level of income. To distinguish between these two types of estimations we include a zero-one type dummy variable COND. However, even for studies of conditional convergence, there is much variety in the types and numbers of explanatory variables used. The strict neo-classical model suggests that differences in the determinants of steady states may be provided by the savings rate, population growth rate and technology. A higher savings rate should lead to more rapid capital accumulation, thereby hastening the onset of diminishing returns. Population growth is expected to speed up convergence because, as the capital-labor ratio is reduced, diminishing returns are expected to set in. Technology has been interpreted liberally with as many as 50 different conditioning variables used in convergence regressions. These often include measures of human capital development (such as years of schooling), openness to trade and variables reflecting industrial structure.

To account for differences in all of the conditioning variables is infeasible given our sample size and the rich variety of explanatory variables that have been used. Therefore, we generated a number of zero-one type dummy variables to control for the ones most commonly used, namely: (1) share of industry and agriculture in GDP (GDPSH), (2) human capital development (HC), (3) investment rate (INV), and (4) population, employment or labor force growth (PLEGR). GDPSH and HC capture technology differences while INV (a proxy for savings) and PLEGR capture other cross-country differences suggested by the theory.[7]

Most of the earlier studies estimate β using simple OLS. As noted in section 2 one problem with this approach is that OLS estimates can be significantly biased if any uncontrolled for effects are correlated with the variable of interest. To account for potential biases and/or to check the robustness of the OLS estimates panel estimation methods have become increasingly common. While the choice among the various panel estimators (FE, RE and GMM) will depend on the researcher's assessment of the appropriateness of the underlying assumptions for each, we feel that the most important aspect between them is that they control, as does the LSDV approach, for time invariant unobserved effects that could be correlated with the estimator of convergence.[8] We therefore generated a simple zero-one type dummy, FE, indicating whether such effects were controlled for without distinguishing between the techniques employed.

Conditional on data availability studies have examined convergence over a variety of sample periods. Moreover, an important aspect of many studies has been to specifically investigate changes in the rate of convergence over time by estimating convergence across

[7] One should note that with these are not trying to decompose the overall effect of the COND variable into all of its components, but rather are isolating the effects of specific variables.

sub-periods of the sample. This serves as a test of robustness and allows the researcher to ascertain whether there are any within sample variations. While a group of regions or countries may exhibit no convergence over the entire sample period, there may be convergence in sub-periods. For instance, an economy that is open to international trade and competition is often one that is successful in obtaining technology transfers from abroad, provided that there is sufficient human capital to absorb the technology. The extent of globalization will have differed over time and may therefore affect the rate of convergence. Given this we were careful to include estimates not only for the entire sample period but also for sub-periods.

It is also possible that convergence is not a linear function of the span of time over which it is estimated. In order to capture this, and the aforementioned aspect of time dimensional differences, two control variables are included. SPAN is the number of years covered by each estimation, i.e. the difference between the start and end year of the period or sub period. The other time variable, AYEAR, is the average year considered or the midpoint between the beginning and the end year for the full period.

A zero-one type variable LDC is also included to control for the fact that some studies, both intra-national and cross-national, exclusively focus on a developing country or a set of developing countries, respectively. This may potentially be important if developing countries start from a lower base and this influences the rate of convergence across countries and regions. There may also be differences in the value of β due to sample size

[8] Distinguishing between all the estimators is infeasible given our sample size. It is important to note however that apart from the LSDV approach the most common other approach was the simple fixed effects estimator,

differences. In line with other meta-analyses, such as Card and Krueger (1995), the square root of the degrees of freedom, DOF, is included as an independent variable.

A number of other meta-independent variables are utilized that are specific to the two groups of studies. As mentioned above, we have included what we term ultra-national studies in our set of estimates from cross-country studies. Hence, we investigate whether ultra-national studies are likely to derive a different rate of convergence by including the simple zero-one type dummy variable, ULTRA. Also, a large number of cross-national studies have used the Summers and Heston panel data set, which provides a rich set of information with which to estimate convergence. We generated a simple zero-one type dummy, SH, to capture this.[9]

While in general the choice of countries as units of investigation of convergence can be justified in terms of national sovereignty, one could argue that comparing estimated rates of convergence for regional units within countries might not be as clear-cut. For example, regions (states) in the US are quite different in size to regions in Japan. It is, of course, difficult to arrive at a summary statistic that captures differences in regional characteristics across studies. As a simple rough and ready measure we calculated the average size of regional units within a country, by dividing the geographical area of the country by the number of regions (used in the study), AAREA.

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where variables are measured as deviations from their mean.

[9] In studies of regional (intra-national) convergence the data is usually taken from national organizations. Some studies of intra-national convergence that include countries that form part of the European Union obtain data from the database CRENOS as well as domestic sources.

Tables 1 and 2 show the means of the explanatory variables for the estimates used in each study. Table 1 reveals that there are 156 estimates cross-national estimates, derived from 25 different papers. The average value of β is 0.0196, but varies significantly across estimates.[10] Table 2 shows a larger set of estimates for studies of intra-national convergence, namely 214 derived from 31 studies. Compared to the cross-national studies, the β estimates derived from intra-national studies are over 50 per cent higher. Graphs of the β estimates over time are shown in Figures 1 and 2. Both graphs show that the variation in rates is considerable (with the variation higher in Figure 2) and that the variance is much larger in later studies compared to earlier ones. This latter finding may reflect the different time spans used or it could be due to a change in estimation technique in more recent work.

4. Results

According to Stanley (2001) MRA is likely to be less problematic than conventional econometric analysis. Even so, there are two issues of concern in this study. First, because the dependent variable is drawn from studies with very different characteristics the error term structure is unlikely to be homoskedastic (Stanley and Jarrell, 1989). Second, because we use multiple estimates of β from the same study the error terms within studies may be correlated even though they will be independent across studies. Accordingly, in computing the standard errors of the estimates we allow for a heteroskedastic error term structure as well as for a non-specified correlation between observations from the same study.[11]

[10] The standard deviation is 0.022.

[11] The model was estimated by OLS using the Huber/White/sandwich estimator in STATA. This procedure produces estimates of variance (and thus standard errors) that are robust to heteroskedasticity as well as any type of correlation that may be present between observations from the same study.

The results of estimating (4) for the sample of convergence rates for the two different groups are given in Table 3. It should be noted that across all specifications the R squared values suggest that the explanatory variables are able to account for a reasonable proportion of differences across estimates, although unsurprisingly a majority of variation remains unexplained.[12] Column 1 contains results for the cross-national sample, including the dummy variable COND instead of the alternative set of conditioning variables mentioned above. For this specification a number of aspects of sample design matter for the rate of convergence found. Specifically, both time dimensional controls are found to be important. Studies that examine earlier time periods, using AYEAR as a proxy, tend to find lower rates of convergence, which may indicate that convergence has not been constant over the time periods examined. Similarly, the rate of convergence is lower the longer the time span of the study, suggesting possibly that the rate of convergence is not a linear function of time. The results also indicate that studies that have used the Summers and Heston data set tend to find lower rates of convergence.

The estimated rate of convergence between developing countries is, ceteris paribus, found to be lower than in studies that compare developed countries and/or developed and developing countries in the same study. Moreover, we find that conditional convergence rates tend to be significantly higher than rates of unconditional convergence. It is also important to control for unobserved effects that may be correlated with the regressors as the estimates associated with these techniques tend to be higher. Finally, the lack of significance on our other explanatory variables suggests that non-linear methods of

[12] For a similar finding see Görg and Strobl (2001).

estimation and studies that allow for geographical cross-sectional units that extend beyond national boundaries are not important.

In the second column of Table 3 the alternative set of conditioning variables are included instead of COND. While our previous results generally still hold we do find that the use of the Summers and Heston data set is no longer a significant determinant. This suggests that its significance in the first specification was due to the fact that this data set also allows the use of a rich set of conditioning variables. In terms of these variables only human capital affects the estimated rate of convergence, specifically by increasing its rate; in other words, failing to control for human capital difference across countries is likely to result in a lower rate of convergence.

In terms of the number of significant variables, the results from the estimation of (4) for the intra-national studies suggest that the set of sample design proxies play less of a role than for the cross-national studies. In column 3, which contains the specification with COND instead of our alternative set of conditioning variables, only the time span and whether a conditional or unconditional specification is employed seem to matter. Specifically, as for the cross-national sample, these tend to decrease and increase the estimated rate of convergence rate, respectively. This is not changed when we include our set of conditioning dummies instead of COND, as shown in column 4. In contrast to the cross-national results, we find GDPSH rather than HC to be important in influencing the reported rate of convergence.[13]

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[13] The intra-national models were also tried with a disaggregated LDC dummy variable (Africa, Latin America and so on) but the results were not improved. Breaking up the sample in terms of LDC/Non-LDC did

A number of meta-analyses in other areas of economics are explicitly concerned with the possibility of publication bias: a tendency for only significant results to be published in journals. This is unlikely to be the case for the literature on β-convergence as many authors report both significant and insignificant results and, moreover, seem to readily use insignificant coefficients to derive and discuss rates of convergence. Nevertheless, we conducted the popular test of regressing the t-statistic from which the rate was derived on the standard error, as these should be unrelated if there is no publication bias.[14] Unsurprisingly, no relationship was found between these two statistics for our sample.[15] We thus investigated the robustness of our results by including only those convergence estimates that either indirectly, or directly in the case of non-linear estimation, were derived from a significant coefficient, where significant is understood to be at least the ten per cent level. These results of this exercise are shown in Table 4. First, in terms of the intra-national sample the results remain robust to excluding all βs derived from insignificant estimates. In contrast, for the cross-national sample human capital no longer serves as a significant explanatory variable for variations in the estimated rate of conditional convergence, although in the full sample this variable was only marginally significant. Overall, Table 4 suggests that using convergence rates derived from insignificant estimates is not misleading.

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not work mainly because of sample size problems (the same applies to a COND/Non-COND split). A number of interaction terms were also tried (including interacting LDC with other variables) but the results were not improved.

[14] See, for instance, Görg and Strobl (2001).

[15] Results are available from the authors on request.

From a more general perspective, one should note that the degrees of freedom variable, DOF, is insignificant in all specifications. As pointed out by Stanley (2001), the inclusion of this variable may be interpreted as an additional independent test for the "existence of an authentic empirical effect in the literature" (p. 142).[16] Accordingly, if the coefficient on this variable is not positive and significant, then this raises concerns about the presence of an authentic empirical phenomenon in the literature rather than just "exploitable artifacts of misspecification" (p. 142). In our case the insignificant results for DOF suggests that the empirical literature on β-convergence may in general suffer from misspecification. To some extent this is already hinted at by the significant coefficient on SPAN, which suggests that convergence may not be a linear function of time as is generally assumed.

5. Conclusion

Many tests of the convergence hypothesis can be found in the empirical convergence literature. Reviews of the literature suggest that the empirical evidence is mixed: sometimes β is positive and significant, sometimes it is positive but not significant and on occasions it is found to be negative. The inconsistency in the findings has prompted Temple (1999) in his review of cross country studies to suggest that poor countries are not catching up to richer ones and that while countries are converging to their own steady states they are doing so at an uncertain rate. While a number of narrative literature reviews have offered possible reasons for the study-to-study variation in the value of β there has not been a formal assessment of the factors influencing estimates of β (the speed of convergence).

[16] This arises because of the asymmetry of classical statistical testing and the relationship between the degrees

In contrast to discursive reviews, a meta-regression analysis of the literature allows the effects of study design and methodology to be quantified and so sheds more light on why there is such study-to-study variation in the value of β. We find that the reported speed of convergence is clearly sensitive to certain aspects of study design, especially the choice of econometric methods, the data used and the time period covered. In particular, we discover that estimates from studies that include developing countries, that cover longer time spans, and that cover earlier time periods tend to be lower. There is also evidence that the Summers and Heston data set produces lower estimates of β, which is likely to reflect the fact that this data set contains a rich set of explanatory variables with which to conduct convergence estimation. Related to this, the choice of an unconditional or conditional specification appears to be an important determinant of the size of the estimates: reported values of β are higher for conditional convergence estimates, thus indicating that countries have different steady states due to differences across countries with regard to technology, population growth rates and so on.

In terms of econometric methodology failing to control for the bias produced by unobserved fixed effects produces lower estimates of the rate of convergence. Relative to cross-national studies of convergence, differences in study design explain little in terms of the variation in the estimated rates of convergence in regional studies. Nevertheless, even in studies of convergence within countries, conditional convergence specifications as well as the time span within which convergence is estimated appear to be important factors.

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freedom and the power of the statistical test (see, Stanley (2001) for details).

More generally, the MRA model is robust to estimation using significant β coefficients only and while estimates of the rate of convergence from insignificant coefficients do not seem to be important for the size of the estimate, there is some evidence of general misspecification in the literature. Our results suggest that part of the reason for this may be that, contrary to the common implicit assumption in the specifications from which estimates are derived, the rate of convergence may not be a linear function of the time period over which the convergence rate is estimated.

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Table 1: Sample and Means of Cross-National Estimates

Study	Scope	Nr.	COEFF	ULTRA	NL	DOF(sqr)	SH	LDC	FE	AYEAR	SPAN	COND	GDPSH	HC	INV	PLEGR
Andres et al (1996)	OECD	12	0.0223	0.00	1.00	7.5	1.00	0.00	0.50	1973	25	1.00	0.00	0.08	0.00	0.00
Armstrong (1995)	EU Regions	4	0.0218	1.00	1.00	8.9	0.00	0.00	0.00	1970	10	0.00	0.00	0.00	0.00	0.00
Barro (1991)	World	6	0.0088	0.00	0.00	9.4	1.00	0.00	0.00	1974	22	1.00	0.00	1.00	0.33	0.00
Barro & Sala-i-M. (1991)	EU Regions	5	0.0335	1.00	1.00	10.1	0.00	0.00	0.20	1969	14	0.00	0.00	0.00	0.00	0.00
Barro & Sala-i-Mart. (1992)	World	1	-0.0037	0.00	1.00	6.8	0.00	0.00	0.00	1973	25	0.00	0.00	0.00	0.00	0.00
Ben-David (1995b)	OECD	2	0.0132	0.00	0.00	4.1	1.00	0.00	0.00	1959	58	0.00	0.00	0.00	0.00	0.00
Ben-David (1995b)	World	1	-0.0044	0.00	0.00	10.8	1.00	0.00	0.00	1973	26	0.00	0.00	0.00	0.00	0.00
Berthelemy & Var. (1997)	World	1	0.0125	0.00	0.00	21.5	1.00	0.00	1.00	1975	30	1.00	0.00	1.00	1.00	1.00
Berthelemy and Var. (1996)	World	1	0.0149	0.00	0.00	9.6	1.00	0.00	0.00	1978	35	1.00	0.00	0.00	0.00	0.00
Caselli et al (1996)	World	13	0.0439	0.00	0.00	18.7	1.00	0.00	1.00	1973	25	1.00	0.00	0.38	1.00	0.62
Cashin (1995)	Australasia	6	0.0238	0.00	0.00	2.2	0.00	0.00	0.17	1930	77	0.00	0.00	0.00	0.00	0.00
Cashin & Loayza	South Pacific	4	0.0075	0.00	0.00	5.9	1.00	1.00	1.00	1981	21	1.00	0.00	0.00	1.00	0.00

(1995)																
de la Fuente (1995)	OECD	1	0.0300	0.00	1.00	3.9	1.00	0.00	0.00	1976	25	1.00	0.00	1.00	1.00	0.00
Dobson & Ram. (2002a)	Latin America	10	0.0094	0.00	1.00	4.5	0.00	1.00	0.20	1984	17	0.50	0.50	0.50	0.00	0.00
Dobson & Ram. (2002b)	Latin America	16	0.0066	0.00	1.00	4.5	1.00	1.00	0.13	1975	11	0.50	0.50	0.50	0.50	0.50
Felipe (1999)	Asia	1	-0.0050	0.00	1.00	4.0	1.00	1.00	0.00	1975	30	0.00	0.00	0.00	0.00	0.00
Islam (1995)	N-OECD	6	0.0213	0.00	0.00	15.6	1.00	1.00	0.67	1973	25	1.00	0.00	0.00	1.00	1.00
Islam (1995)	OECD	6	0.0412	0.00	0.00	8.2	1.00	0.00	0.67	1973	25	1.00	0.00	0.00	1.00	1.00
Islam (1995)	World	6	0.0199	0.00	0.00	17.9	1.00	0.00	0.67	1973	25	1.00	0.00	0.00	1.00	1.00
Khan and Kumar (1993)	LDCs	17	0.0118	0.00	0.00	9.5	1.00	1.00	0.00	1980	14	1.00	0.00	0.47	1.00	1.00
Knight et al (1993)	LDCs	2	0.0625	0.00	0.00	19.2	1.00	1.00	1.00	1973	25	1.00	0.00	1.00	1.00	1.00
Knight et al (1993)	World	3	0.0556	0.00	0.00	17.8	1.00	0.00	0.67	1973	25	1.00	0.00	1.00	1.00	1.00
Lee et al (1998)	OECD	2	0.0211	0.00	0.00	10.0	1.00	0.00	1.00	1970	40	1.00	0.00	0.00	1.00	1.00
Mankiw et al (1992)	LDCs	4	0.0118	0.00	0.00	8.5	1.00	1.00	0.00	1973	25	0.75	0.00	0.00	0.75	0.75
Mankiw et al (1992)	OECD	4	0.0187	0.00	0.00	4.3	1.00	0.00	0.00	1973	25	0.75	0.00	0.00	0.75	0.75
Mankiw et al (1992)	World	4	0.0076	0.00	0.00	9.7	1.00	0.00	0.00	1973	25	0.75	0.00	0.00	0.75	0.75

Nevin & Gouyette (1995)	EU Regions	5	0.0146	1.00	1.00	11.2	0.00	0.00	0.00	1983	7	0.00	0.00	0.00	0.00	0.00
Paci (1997)	EU Regions	1	0.0016	1.00	0.00	10.3	0.00	0.00	0.00	1985	10	0.00	0.00	0.00	0.00	0.00
Sachs & Warner (1995)	World	1	0.0130	0.00	0.00	10.7	1.00	0.00	0.00	1980	19	0.00	0.00	0.00	0.00	0.00
Sala-i-Martin (1995, 1996)	EU Regions	3	0.0160	1.00	1.00	11.6	0.00	0.00	0.33	1970	40	0.67	0.00	0.67	0.00	0.00
Sala-i-Martin (1995, 1996)	OECD	3	0.0240	0.00	1.00	4.0	0.33	0.00	0.00	1975	30	0.67	0.00	0.67	0.00	0.00
Sala-i-Martin (1995, 1996)	World	5	0.0142	0.00	1.00	13.4	0.20	0.00	0.40	1975	30	0.80	0.00	0.80	0.00	0.00
Total/Av.		*156*	*0.0196*	*0.12*	*0.42*	*9.6*	*0.74*	*0.38*	*0.33*	*1973*	*23*	*0.71*	*0.08*	*0.31*	*0.51*	*0.44*

Note: Listing includes a few ultra-national studies.

Key: Nr = number of estimates of β; COEFF = average value of β; ULTRA = ultra-national study (regions reach beyond national boundaries; NL = (direct) non-linear estimation of β; DOF(sqr) = degrees of freedom; SH = Summers and Heston data used; LDC = developing country (or countries) study; FE = estimation controls for time invariant unobserved effects; AYEAR = average year of sample; SPAN = number of years covered by each estimation; COND = conditional convergence estimation; GDPSH = share of industry and agriculture in GDP; HC = human capital measure; INV = rate of investment; PLEGR = population, employment or labor force growth.

Table 2: Sample and Means of Intra-National Estimates

Study	Scope	Nr.	COEFF	NL	DOF(sqr)	LDC	FE	AYEAR	SPAN	COND	GDPSH	HC	INV	PLEGR	AAREA
Afxentiou & Serl. (1998)	Canadian provinces	1	0.0146	0.00	4.2	0	0.00	1976	30	0.00	0.00	0.00	0.00	0.00	498807
Azzoni (2001)	Brazilian regions	1	0.0056	1.00	4.2	1	0.00	1967	56	0.00	0.00	0.00	0.00	0.00	425598
Barro, Sala-i-Martin (1991)	US states	10	0.0149	1.00	8.1	0	0.10	1942	22	0.00	0.00	0.00	0.00	0.00	204874
Barro, Sala-i-Martin (1992)	US states	17	0.0199	1.00	8.0	0	0.12	1953	24	0.00	0.00	0.00	0.00	0.00	200606
Ben-David (1995a)	US regions	1	0.0375	0.00	2.4	0	0.00	1975	23	0.00	0.00	0.00	0.00	0.00	1203636
Ben-David (1995a)	US states	1	0.0307	0.00	6.8	0	0.00	1975	23	0.00	0.00	0.00	0.00	0.00	200606
Cardenas & Ponton (1995)	Columbian regions	12	0.0342	1.00	5.2	1	0.17	1973	19	0.42	0.42	0.00	0.00	0.00	47455
Chen & Fleish. (1996)	Chinese regions	5	0.0266	0.00	5.0	1	0.20	1980	25	0.60	0.00	0.60	0.60	0.60	3354
Choi & Li (2000)	Chinese regions	4	0.0475	0.00	6.4	1	1.00	1986	16	1.00	0.00	0.50	1.00	1.00	5241
Dayal-Gul. & Husain (2000)	Chinese regions	14	0.0106	0.93	4.7	1	0.00	1988	8	0.64	0.29	0.00	0.64	0.00	2995
Esquivel (1999)	Mexican regions	5	0.0140	1.00	5.5	1	0.00	1971	28	0.00	0.00	0.00	0.00	0.00	61642
Ferreira (2000)	Brazilian regions	16	0.0400	0.00	4.7	1	0.19	1982	19	0.75	0.00	0.75	0.50	0.56	368235
Hofer & Worgot.(1997)	Austrian districts	7	0.0093	1.00	10.0	0	0.14	1976	18	0.00	0.00	0.00	0.00	0.00	998
Hossain(2000)	Bangladesh regions	3	-0.001	0.00	4.4	1	0.00	1990	10	0.00	0.00	0.00	0.00	0.00	6857
Izreali(1997)	US states	9	0.0121	0.00	6.8	0	0.00	1979	18	0.44	0.00	0.44	0.00	0.00	192582

Jian et al (1996)	Chinese regions	3	0.0040	0.00	4.1	1	0.00	1972	15	0.00	0.00	0.00	0.00	0.00	4725
Juan Ramon (1996)	Mexican regions	5	0.0136	1.00	5.5	1	0.00	1982	10	0.00	0.00	0.00	0.00	0.00	61642
Kangasharju (1998)	Finnish regions	6	0.0242	1.00	9.3	0	0.00	1971	25	0.00	0.00	0.00	0.00	0.00	3830
Li et al (1998)	Chinese regions	4	0.0297	0.00	6.6	1	0.50	1987	17	0.75	0.00	0.75	0.75	0.75	2892
Mauro & Podr. (1994)	Italian regions	4	0.0012	1.00	4.2	0	0.00	1972	20	0.00	0.00	0.00	0.00	0.00	15062
Nagaraj et al (2000)	Indian states	5	0.0206	0.20	19.4	1	1.00	1982	24	1.00	0.00	0.00	0.00	0.00	193388
Paci & Piglia. (1997)	Italian regions	1	0.0003	0.00	4.2	0	0.00	1981	22	0.00	0.00	0.00	0.00	0.00	15062
Paci & Saba (1998)	Italian regions	4	0.0100	0.00	4.2	0	0.00	1970	21	0.00	0.00	0.00	0.00	0.00	15062
Pekkala (1999)	Finnish provinces	7	0.0249	1.00	3.2	0	0.00	1979	15	0.00	0.00	0.00	0.00	0.00	28086
Persson (1997)	Swedish regions	11	0.0367	1.00	5.5	0	0.09	1948	22	0.00	0.00	0.00	0.00	0.00	18749
Sala-i-Martin (1995, 1996)	French provinces	3	0.0157	1.00	5.3	0	0.33	1970	40	0.67	0.00	0.67	0.00	0.00	26049
Sala-i-Martin (1995, 1996)	German lander	3	0.0147	1.00	3.5	0	0.33	1970	40	0.67	0.00	0.67	0.00	0.00	32456
Sala-i-Martin (1995, 1996)	Italian regions	3	0.0120	1.00	5.1	0	0.33	1970	40	0.67	0.00	0.67	0.00	0.00	15062
Sala-i-Martin (1995, 1996)	Japanese regions	3	0.0230	1.00	8.9	0	0.33	1973	35	0.67	0.00	0.67	0.00	0.00	8039
Sala-i-Martin (1995, 1996)	Spanish regions	3	0.0210	1.00	4.6	0	0.33	1971	32	0.67	0.00	0.67	0.00	0.00	29693
Sala-i-Martin (1995, 1996)	UK counties	3	0.0263	1.00	3.5	0	0.33	1970	40	0.67	0.00	0.67	0.00	0.00	906922

Sala-i-Martin (1995, 1996)	US states	3	0.0200	1.00	11.3	0	0.33	1935	110	0.67	0.00	0.67	0.00	0.00	200606
Shioji(2001)	Japanese regions	6	0.0888	0.00	17.7	0	1.00	1978	35	1.00	0.00	0.00	0.00	0.00	8214
Shioji(2001)	US states	6	0.2288	0.00	15.2	0	1.00	1983	20	1.00	0.00	0.17	0.00	0.00	200606
Siriopoulas & Ast. (1998)	Greek regions	9	0.0014	1.00	3.2	0	0.00	1983	17	0.67	0.00	0.00	0.67	0.00	10149
Wei et al (2001)	Chinese regions	4	0.0927	0.00	16.0	1	1.00	1991	9	0.75	0.00	0.75	0.75	0.00	3106
Yao and Zhang (2001)	Chinese regions	12	0.0413	0.00	9.6	1	0.83	1987	17	1.00	0.00	0.50	1.00	1.00	2795
Total		*214*	*0.0308*	*0.60*	*7.2*	*0.43*	*0.26*	*1973*	*22*	*0.43*	*0.04*	*0.22*	*0.22*	*0.14*	*108909*

Key: Nr = number of estimates of β; COEFF = average value of β; NL = (direct) non-linear estimation of β; DOF(sqr) = degrees of freedom; LDC = developing country (or countries) study; FE = estimation controls for time invariant unobserved effects; AYEAR = average year of sample; SPAN = number of years covered by each estimation; COND = conditional convergence estimation; GDPSH = share of industry and agriculture in GDP; HC = human capital measure; INV = rate of investment; PLEGR = population, employment or labor force growth; AAREA = geographical area of country/number of regions.

Table 3: Results of Meta-Regression

	(1)	(2)	(3)	(4)
SAMPLE:	**CROSS**	**CROSS**	**INTRA**	**INTRA**
NL	-0.005	-0.003	-0.014	-0.017
	(0.004)	(0.005)	(0.010)	(0.015)
DOF(sqr)/1000	0.055	-0.256	2.635	2.732
	(0.841)	(0.758)	(2.126)	(1.629)
SH	-0.006***	-0.005		
	(0.002)	(0.003)		
LDC	-0.008**	-0.010***	-0.016	-0.016
	(0.003)	(0.003)	(0.017)	(0.016)
FE	0.016*	0.019*	0.016	0.022
	(0.009)	(0.009)	(0.015)	(0.022)
AYEAR/1000	-0.467***	-0.455***	-0.030	0.025
	(0.136)	(0.129)	(0.146)	(0.156)
SPAN/1000	-0.326***	-0.323***	-0.389**	-0.402**
	(0.073)	(0.070)	(0.188)	(0.181)
COND	0.009***		0.020**	
	(0.003)		(0.009)	
GDPSH		-0.006		0.019*
		(0.009)		(0.010)
HC		0.011*		0.017
		(0.006)		(0.013)
INV		0.011		0.004
		(0.013)		(0.009)
PLEGR		-0.003		-0.010
		(0.015)		(0.016)
ULTRA	0.004	0.003		
	(0.005)	(0.005)		
AAREA/1000000			0.023	0.020
			(0.019)	(0.016)
Constant	0.945***	0.922***	0.080	-0.024
	(0.260)	(0.250)	(0.284)	(0.297)
Observations	156	156	214	214
F-Test	13.56***	25.51***	2.74**	5.68**
R-squared	0.27	0.31	0.30	0.29

Notes: (1) ***, **, and * represent one, five, and ten per cent significance levels, respectively; (2) White adjusted standard errors in parentheses.

Table 4: Results of Meta-Regression for Significant Estimates Only

	(1)	(2)	(3)	(4)
SAMPLE:	**CROSS**	**CROSS**	**INTRA**	**INTRA**
NL	-0.007	-0.002	-0.019	-0.023
	(0.005)	(0.005)	(0.012)	(0.016)
DOF(sqr)/1000	-0.527	-0.768	2.036	2.201
	(0.874)	(0.796)	(2.266)	(1.817)
SH	-0.007***	-0.006		
	(0.002)	(0.004)		
LDC	-0.006	-0.008**	-0.023	-0.025
	(0.004)	(0.004)	(0.019)	(0.018)
FE	0.022**	0.023**	0.020	0.026
	(0.009)	(0.010)	(0.017)	(0.022)
AYEAR/1000	-0.419**	-0.457**	0.106	0.167
	(0.167)	(0.163)	(0.158)	(0.163)
SPAN/1000	-0.404***	-0.388***	-0.485**	-0.457**
	(0.088)	(0.084)	(0.212)	(0.221)
COND	0.008**		0.019**	
	(0.004)		(0.009)	
GDPSH		-0.003		0.023*
		(0.010)		(0.012)
HC		0.010		0.006
		(0.007)		(0.010)
INV		0.017		0.011
		(0.012)		(0.011)
PLEGR		-0.008		-0.005
		(0.015)		(0.016)
ULTRA	0.003	0.004		
	(0.005)	(0.006)		
AAREA/1000000			0.006	0.010
			(0.018)	(0.016)
Constant	0.860**	0.932***	-0.170	-0.285
	(0.320)	(0.314)	(0.305)	(0.308)
Observations	128	128	173	173
F-Test	11.23***	11.42***	5.35**	6.10**
R-squared	0.23	0.29	0.34	0.33

Notes: (1) ***, **, and * represent one, five, and ten per cent significance levels, respectively; (2) White adjusted standard errors in parentheses.

Figure 1 – Cross-National Studies

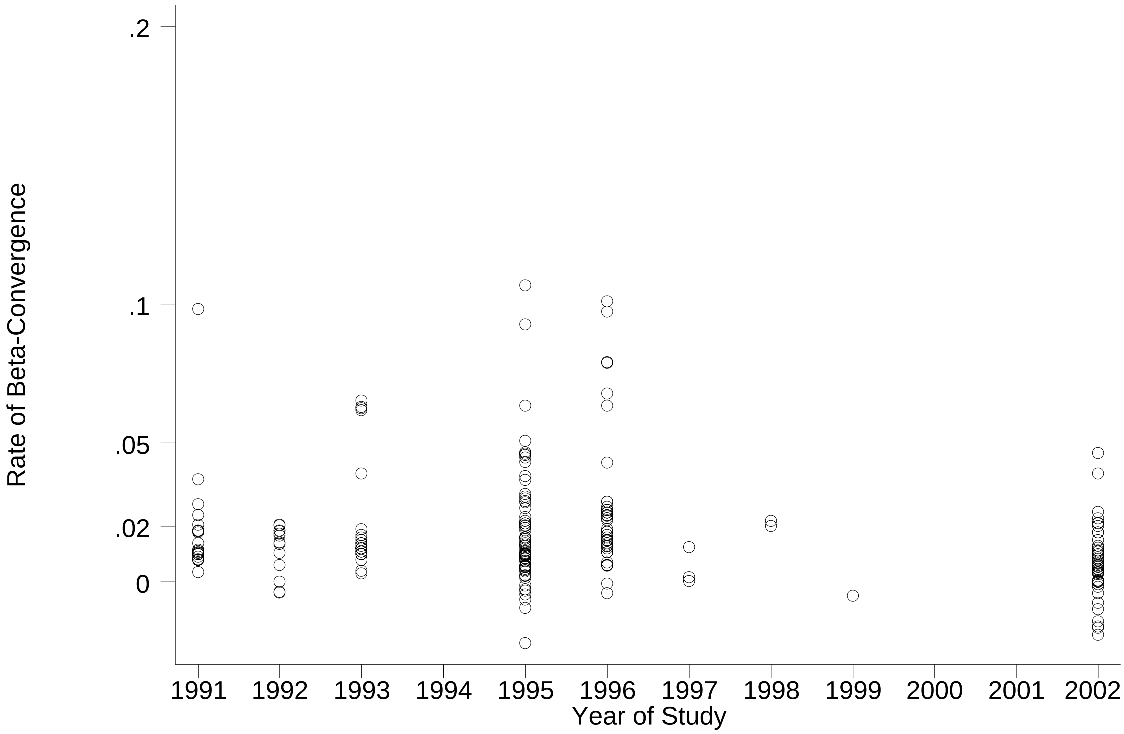

Figure 2 – Intra-National Studies