Cross-Regional Convergence:

Review of Methods and Empirics

by

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An essay submitted to the Department of Economics

in partial fulfillment of the requirements for

the degree of Master of Arts

Queen's University

Kingston, Ontario, Canada

August 2013

Acknowledgments

I would like to express my deepest appreciation to my supervisor Professor Huw Lloyd-Ellis for his invaluable guidance and supervision.

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1. Introduction:

One of the central topics in the literature on economic growth is convergence. This literature addresses the general issue of whether poor countries or regions tend to grow faster than rich ones. Related questions include whether or not poor economies remain poor over long periods of time, how quickly do poor economies catch up with rich ones, and what factors determine the rate of convergence. The convergence literature addresses all these important questions which are paramount for human welfare.

According to the neoclassical growth model, convergence is an implication of the assumption of diminishing returns to capital. The important issue in this regard is the methodology used in testing for the existence and extent of convergence. Convergence depends on the steady states of economies and testing for convergence assumes that economies are moving towards these steady states. Studying the correlation between the initial level of income and subsequent growth is one way of testing convergence. Poor economies with low levels of capital have a higher marginal product of capital because of diminishing marginal returns to capital, and for the same saving rate, are predicted to have higher growth rates than those with more initial capital. According to the theory Poor countries should grow faster initially and then decelerate as they catch up with richer countries. Therefore, negative cross-country correlation between initial levels of income and subsequent growth is one indication of convergences.

Researchers in the convergence literature have adopted various different definitions and methodologies. Consequently, they have found different results and have come to different conclusions. Nevertheless, the literature has reached some consensus on the interpretation of empirical convergence results. Islam (2003) provides a comprehensive background by studying the literature from a history of thought point of view and tries to extend and update previous surveys. His paper defines different concepts of convergence and classifies the methodologies used to investigate them.

This paper is organized as follows: in section 2, a brief survey of convergence studies is presented. In section 3, I discuss two important papers that present the framework of neoclassical growth and then the papers that critique them. In section 4, I survey the dynamic panel estimation approach to convergence, focusing especially on the empirical methodologies adopted by different authors. Section 5 explains the more recent spatial dynamic panel approach. Section 6 concludes the paper.

2. A Brief survey of convergence studies:

By extending the neoclassical growth conception of technology to the world level, cross-country convergence can be thought about in two different ways: convergence in terms of growth rates and in terms of income levels. The key neoclassical assumptions characterizing technological progress are: no resources for generating the technological innovations, equal benefits for everybody and no compensation for benefiting from it.[1] Thus all countries share in global technological progress at the same rate and can grow equally in the steady state. Consequently we obtain convergence in growth rates. If we assume that all countries have identical aggregate production functions we can conclude that they have identical income levels in steady state and so we obtain convergence in terms of income level.

Another concept is β-convergence which implies convergence in both growth rates and income levels by assuming diminishing returns. Under this assumption amongst

[1] Islam, N.(2003)

countries with equivalent saving rates the poorer countries grow faster. The methodology of running a cross-country regression of growth rates on initial income levels uses this concept. If the coefficient from such a regression is negative then the countries in the sample are said to exhibit β-convergence.

The most important notions of convergence are conditional and unconditional convergence derived from the Solow model under the assumption of a Cobb-Douglas production function. Conditional convergence means that some determinants of the steady state levels of income per capita are different across economies. In contrast, they are the same across economies in the case of unconditional convergence. The sign of β is expected to be negative in convergence regressions for both conditional and unconditional convergence but, in the former case, we need to control for factors that cause differences in the steady state. Conditional convergence implies that each economy converges to its own unique steady state level while unconditional convergence means all economies converge to one identical steady state level. Another notion of convergence, club convergence, allows for the possibility of multiple steady states that depend on certain elements such as the initial location or some other attribute. Income convergence may not only be the outcome of capital deepening but can also be the result of technological catch-up which could be measured by total factor productivity (TFP). According to that perspective, TFP convergence investigates whether countries have come closer in terms of TFP levels.

The methodology of investigating convergence initially consisted of estimating cross-country regressions that were not derived formally from theoretical models of growth. Baumol (1986) estimates a negative coefficient on initial income in a long run sample of 16 OECD countries suggesting the presence of unconditional convergence. Other studies such as Kormendi and Meguire (1985) and Grier and Tullock (1989) yielded negative values of β that could be interpreted as conditional convergence. Barro (1991) considers the convergence issue from the neoclassical perspective and introduced measures of human capital as an important variable in convergence research. He estimates a negative and significant coefficient for initial income level when he includes human capital.

Mankiw, Romer and Weil (1992) and Barro and Sala-i-Martin(1992), hereafter MRW and BS, respectively, each derive a formal specification of the convergence regression from a version of neoclassical growth theory. MRW use the original Solow-Swan model while BS work with the Cass-Koopman's model. MRW augment the basic Solow model by including human capital as an argument in the production function in addition to physical capital. The augmented Solow model implies a value for the estimated capital share (0.48 for the nonoil sample[2]) and the speed of convergence (around 0.2). The formal convergence regression is not only used to investigate convergence across countries but also used across regions. Barro and Sala-i-Martin use the neoclassical growth model as a framework to study convergence across US states. They find evidence of significant convergence at an average rate of 2 percent per year. Club convergence is also investigated by formal cross section equations in the study of Durlauf and Johnson (1995).

[2] MRW consider three samples of countries. 1) "Nonoil" consists of a sample of 98 countries that do not export oil s, 2) "Intermediate" consists of 75 middle-income countries, and 3) OECD consists of 22 rich industrial countries.

Due to ease of implementation, the formal cross section regression has become a useful and popular workhorse for examining issues associated with growth other than the convergence. Benhabib and Spiegel (1994) study the effect of human capital by applying the MRW model. Klenow and Rodriguez-Claire (1997) critique the specific measure of human capital used by MRW by examining the impact of alternative measures of human capital on the convergence results presented in MRW.. Temple and Johnson (1998) study the role of social capital by using the MRW specification. Fischer (2009) extends the MRW model by accounting for technological independence among regional economies. These are just a small number of the many papers that use formal cross section specifications and this line of research is still continuing.

So far all of these studies deal with cross sectional data, and do not take into account heterogeneity in preferences and technology across economies. Some of these differences are not measurable but they could be considered as unobservable individual effects in a panel estimation approach. In order to deal with these differences convergence research has evolved from cross sectional analysis to the use of panel data estimation frameworks. Islam (1995) uses a panel estimation approach and yields higher rate of convergence than the single cross-country regression. We will focus on Islam's work and approach precisely further.

Islam (1995) exhibits a good treatment of the correlated individual effect, but is affected by endogeneity bias. There is a strong argument that a subset of the explanatory variables should be expected to have endogeneity. Caselli, Esquivel and Lefort (1996) address these two problems by applying a first-differenced generalized method of moments to dynamic panel data models. The general form of their approach is as follows:

write the regression equation as a dynamic panel data mode, take first differences in order to delete unobserved individual effect, and then instrument the right hand side explanatory variables using levels of the series lagged two periods or more. Bond, Hoeffler, and Temple (2001) argue that first differenced GMM estimator appears to be problematic since lagged levels of the variables are only weak instruments. Hence, they propose a more plausible approach which is typically the referred to as "system GMM".

In addition to heterogeneity in production, institutions and preferences motivating the use of the panel data model, there are some other problems implied by the geographical dimension of the data. Yu and Lee (2012) study regional growth convergence in the US economy using a spatial dynamic panel estimation approach. All the studies prior to this one assume that economies are independent. In an open economy, technological advances, labor and capital may be expected to move from one economy to the others. Spatial panel data models take into account spatial dependence: ignoring that dependence may lead to unreliable statistical inference. Yu and Lee's (2012) spatial panel estimation model approach to studying growth convergence in an open economy will be discussed in more detail later in this paper.

In this literature review paper my main focus is on the key methods used to investigate convergence across countries and regions. The papers that are presented here all track developing trends in the measurement of the speed of convergence. In other words, they extend and criticize previous research.

3. Cross-sectional regression:

3.1. Mankiw, Romer and Weil (1992):

The modern empirical growth literature starts with the work of Mankiw, Romer and Weil (1992) who derive an explicit formulation of conditional convergence. Based on other estimates, MRW argue that Solow's neoclassical growth model with decreasing returns to both physical and human capital is consistent with the evidence.

The basic Solow model predicts that steady state levels of income per capita depend on the saving rate and the population growth rate. Since these vary across countries, they generate different steady states. The Solow model predicts that the saving rate influences the steady state level of income per capita positively and population growth influences it negatively.

3.1.1. Model, data and results:

Aggregate output is assumed to be produced using with effective labor and capital. A Cobb-Douglas production function is considered where at time t output, Y, is given by:

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}$$

Here K is the stock of capital, L is labor effort and A represents the level of technology. The rates of technological progress (g), population growth (n) and capital depreciation (δ) are all constant and exogenous and the economy is closed. Finally, there is an exogenous and constant rate of saving s.

The steady state level of output and capital are obtained from the dynamics of capital stock. Letting $ln(A_0) + gt = a + \varepsilon$,the Solow model implies that the log of output per worker can be expressed as:

$$\ln\left[\frac{Y}{L}\right] = a + \frac{\alpha}{1-\alpha}\ln s - \frac{\alpha}{1-\alpha}\ln(n + g + \delta) + \varepsilon \qquad (1)$$

MRW assume although g and δ are constant across countries, A_0 reflects technology, resources endowments, climate and institutions and may differ across countries.

This formulation illustrates how differing saving and labor force growth rates can explain the differences in the current per capita income across countries by assuming that the countries are currently in their steady states. In other words, MRW try to investigate whether higher saving rates and lower $n+g+\delta$ accompany higher income.

In MRW, equation (1) is estimated by ordinary least squares (OLS) under the assumption that s and n are independent of ε. They argue in support of this assumption in three ways. First, permanent differences in the level of technology under isoelastic utility do not affect saving rates or population growth rates. Second, this assumption makes it possible to test various informal judgments of the relationship between savings, population growth and income. Third, since the above specification gives the sign and magnitude of coefficients, it is possible to test the above mentioned identifying assumption.

They use a data set that includes real income, government and private consumption, investment and population from the Real National Accounts constructed by Summers and Heston (1988). They use the average rate of growth of the working age population to measure n, s is the average share of real investment in real GDP, and Y/L is real GDP I 1985 divided by the working age population in that year. Three samples of countries are considered: a full sample of 98 countries for which data are available excluding oil producer countries (nonoil countries), a sample of 75 intermediate income countries, whose the measurement error is likely to be a greater problem,, and a sample of 22 OECD countries.

MRW's empirical evidence supports the direction of the impacts implied by (1) but finds that their magnitudes are overestimated relative to the predictions of the textbook Solow model with typical values for the capital share. To address this problem, MRW augment the Solow model by including human capital in the production function.

The steady state levels of human and physical capital are obtained from dynamic equations and by substituting them into the production function and taking logs, the income per worker is determined by:

$$\ln\left[\frac{Y_t}{L_t}\right] = lnA_0 + gt + \frac{\alpha}{1-\alpha-\beta}\ln s_k + \frac{\beta}{1-\alpha-\beta}\ln s_h - \frac{\alpha+\beta}{1-\alpha}\ln(n+g+\delta) \qquad (2)$$

They focus on human capital investment in the form of education. The percentage of the working-age population in secondary school is used as the proxy for the rate of human capital accumulation. This data is obtained from UNESCO yearbook. MRW find that including human capital accumulation reduces the estimated influences of saving and population growth. They conclude that even though the measure of human capital is not very precise, the results of the augmented Solow model can explain a large part of the model's residual variance.

MRW use the augmented Solow model to examine whether the Solow model can explain convergence in cross country evidence. They try to generalize their results to account for the behavior out of the steady state by assuming that 1985 was the steady state. Barro (1989) showed that by controlling the differences in the level of human capital, the correlation between the initial level of income and subsequent growth turned to be negative. MRW find the similar results by explaining it in the explicit formulation. They emphasize that convergence is not predicted by the Solow model but rather conditional convergence after controlling for the determinants of the steady state. Determinants of the steady state including investment in human capital, savings and population growth cause different steady states among countries. They basically regress the subsequent growth rate as the dependent variable on the initial level of income as the prime explanatory variable and other variables determining the steady state in the Solow model. For this purpose, the rate of convergence (λ) in the Solow model is derived by approximating the model around the steady state level of income per capita, y^*. In particular, the growth rate of per capita income is given by

$$\frac{d\ lny_t}{dt} = \lambda[\ln(y^*) - \ln(y_t)]$$

where:

$$\lambda = (\mathrm{n} + \mathrm{g} + \delta)(1 - \alpha - \beta)$$

The behavior of a country's growth rate in a neighborhood of the steady state is therefore given by:

$$\ln(y_t) - \ln(y_0) = \left(1 - e^{-\lambda t}\right)\frac{\alpha}{1-\alpha-\beta}\ln(s_k) + \left(1 - e^{-\lambda t}\right)\frac{\beta}{1-\alpha-\beta}\ln(s_h) - \left(1 - e^{-\lambda t}\right)\frac{\alpha+\beta}{1-\alpha-\beta}\ln(\mathrm{n} + \mathrm{g} + \delta) - \left(1 - e^{-\lambda t}\right)\ln(y_0) \qquad (3)$$

They conclude that after taking into account the differences in saving and population growth rates, there is convergence at the rate that the model predicts. Poor countries converge at a higher rate and tend to have higher rates of return on physical and human capital. Therefore, the assumption of decreasing returns of capital can explain cross country variation.

Although, the rate of convergence implied by the augmented Solow model is higher than that of the basic Solow model, it is slower than predicted by the text book Solow model.

3.2. Barro and Sala-i-Martin (1992):

Barro and Sala-i-Martin study convergence across 48 US states using the Ramsey growth model as a framework. They observe clear evidence of convergence in US states' data, meaning that poor states tend to grow faster than rich states. They provide a brief sketch of the neoclassical growth model they use to investigate convergence. As mentioned before, they focus on the inverse relation between initial level of output or income per capita and the per capita growth rate.

3.2.1. Theory:

The Cobb-Douglas production function and the dynamics of physical capital are in the common form of the neoclassical growth model discussed earlier. The difference is that the saving rate is endogenous. The transitional dynamics are given by the solution for $\log(\hat{y}_t)$ in the log linearized approximation to the model, where $\hat{y}$ is the output per unit of effective labor:

$$\log(\hat{y}_t) = \log(\widehat{y_0}).\, e^{-\beta t} + \log(\hat{y}^*)(1 - e^{-\beta t})$$

Here, β is the speed of adjustment to the steady state and is given by:

$$2\beta = \{\psi^2 + 4(\frac{1-\alpha}{\theta})(\rho + \delta + \theta g) \times \left[\frac{\rho + \delta + \theta g}{\alpha} - (n + \delta + g)\right]\}^{1/2} - \psi$$

where ψ=ρ-n-(1-θ)g and $\widehat{y^*}$ is the steady state output per unit of effective labor. The average growth rate of y over the interval between dates 0 and T is:

$$\frac{1}{T}.\log\left[\frac{y_T}{y_0}\right] = g + \frac{1-e^{-\beta t}}{T}.\log\left[\frac{\hat{y}^*}{\hat{y}_0}\right] \qquad (4)$$

From above equation, it may be seen that a higher value of β implies a higher speed of convergence to the steady state. Conditional convergence is implied by this model since, for given values of g and $\hat{y}^*$, the lower value of y_0 implies a higher growth rate. $\hat{y}_0$ relates to g and $\hat{y}^*$ which may differ across economies. BS state that it is very difficult to hold fixed the differences in g and $\hat{y}^*$ in cross country regressions in order to estimate β, while in study of US states, the variations in g and $\hat{y}^*$ are likely to be minor so that absolute and conditional convergence need not be distinguished.

The diminishing returns to capital are an important element of convergence in the neoclassical growth model. The share of capital α could show the extent of diminishing returns and has a strong impact on β. BS show that by raising the α to unity, diminishing returns disappear and the speed of convergence decreases.

They assume that β is identical across US states, although it could be different. Homogeneity of preferences and technologies across US states is consistent with this assumption. Moreover, they show in theory that pure differences in the level of technology do not affect β. Finally, they assume that g and $\hat{y}^*$ are the same for all states. These assumptions mean that, with positive β, poor states tend to grow faster than rich states.

3.2.2. Data and empirical results:

Two different measures of output per worker are considered. The first one is per capita personal income which is available for 48 states since 1929. The second one is per capita gross state product (GSP) and is available from 1963 and 1986. The main difference of these two measurements is capital income. In the GSP data, capital income is attributed to the state in which the business activity occurs, whereas in the personal income data it is attributed to the state of asset holders.

The average growth rate over the interval between any two points in time t_0 and t_0+T is given by:

$$\frac{1}{T}.\log\left(\frac{y_{i,t0+T}}{y_{i,t0}}\right) = B - \left(\frac{1-e^{-\beta T}}{T}\right).\log\left(y_{i,t0}\right) + u_{i,t0,t0+T} \quad (5)$$

where $y_{i,t}$ is the real per capita income or product, $B = g + \left[\frac{1-e^{-\beta T}}{T}\right].[\log(\hat{y}^{*}) + gt_0]$ is the constant term (assumed to be independent of i), and u_{it} is a disturbance term.

The coefficient on $\log(y_{i,t0})$ depends on T in that, for a given β, it gets smaller as T gets longer. BS use nonlinear least squares to take account of the associated value of T in the form of the above equation and expect to obtain similar estimates of β regardless of the length of the interval. They estimate equation (5) for the US states over various time intervals. The explanatory variables aside from $\log(y_{i,t0})$ are a constant term and three regional dummy variables: south, west, and midwest.

In one case equation (5) is estimated for the time period 1880-1988 and in others for sub-periods of this interval. In each case, they get very different values of β. They impose the restriction that in all sub-periods β is the same. This restriction is rejected by the data. BS examine whether instability of β across samples reflects aggregate disturbances that have different effects on state income. The sectoral composition of income in each state is constructed to hold constant these effects by decomposing the sources of labor income into nine categories. The constructed variable that measures the sectoral composition is given by S_{it}. For the periods before 1930, they use the fraction of national income originating in agriculture as a measure of S_{it} because of the problem of availability of the data for sectoral composition. Therefore, separate series for S_{it} are estimated for each sub-period.

BS assume that by holding s_{it} constant, the error terms are independent across states and over time. By adding the sectoral composition variable in the regression, the estimated β coefficients become more stable across subperiods.

The above equation is also estimated using the growth of per capita GSP for 48 states. Again, they find evidence of convergence.

From the result of these estimations, they conclude that, for the nonmanufacturing sectors, the overall estimates of β are less than 0.02 per year and for manufacturing the estimate are over 0.04 per year.

The convergence features of income and product coincide in a closed economy growth model. They also investigate the convergence effects associated with technological diffusion in an open economy. They allow for capital mobility and also extend the neoclassical growth model by allowing for migration. The results show that, in an open economy version of the neoclassical growth model convergence still occurs.

BS also replicate their study of the US states using cross countries data. Barro(1991) analyzes the growth experience of 98 countries using the data of Summers-Heston(1988). The growth rate of real per capita GDP for 98 countries is regressed over the time period 1960-1985 on the constant and the log of per capita GDP in 1960. The estimated β contrasts with the results for US states since it has a low magnitude and the wrong sign, meaning that rich countries have a small tendency to grow faster than poor countries. Barro (1991) demonstrates that by holding constant some other variables, a significant negative partial relation between the per capita growth rate from 1960 to 1985 and the initial per capita income for 98 countries is obtained. BS note that the set other variables consist of primary and secondary school enrollment rates in 1960, the average ratio of government consumption expenditure to GDP, proxies for political stability and a measure of market distortions. By holding constant these variables, they obtain an estimate of β which is very close to the cross states estimate. Thus the other variables help to hold constant cross sectional differences in the long run values.

In summary, the empirical results support the existence of convergence for the US states over various sub-periods from 1840 to 1988. Using a Longer period of sample data they show that poor economies tend to grow faster in per capita terms than rich economies. By holding constant the region and measures of sectoral composition, the speed of convergence emerges to be around 2 percent, regardless of the time period or whether they use personal income or GSP. The evidence of conditional convergence is found for a sample of 98 countries from 1960 to 1985 only if other variables are held constant.

3.3. Comment and criticism:

There are various objections to the neoclassical growth model. However, the important issue is whether the model can explain the wide variation in econometric experience observed throughout the world. Mankiw (1995) discusses three problems that arise when the neoclassical model has come under attack to understand international experience. First, there is much more variation in international living standard than the model predicts. Second, most studies estimate the rate of convergence to be slower than the rate that the model predicts. Third, the model predicts larger variations in rates of return across countries than is seen in the data.

Mankiw argues that each of these three problems would disappear if the capital share were much higher than one third. This conventional estimate comes from the national income accounts. Now the question here is that why should the capital share be higher?

One argument is that there are positive externalities to capital that raise the capital share above one third. Although, it is hard to understand the magnitude of such an externality, the idea that capital conveys positive externalities is possible. A second argument assumes that the capital share is a broader concept than is suggested by the national income accounts. Mankiw suggests that it is best to interpret the variable capital as including all kinds of capital other than only physical capital. The capital share should include the return to both physical and human capital. Adding the estimate of the human capital share to the physical capital share of one third, the income from all forms of capital is found to be about 80 percent of national income. Thus, in the neoclassical growth model, the capital share should be set at about 0.8. This magnitude makes the neoclassical model conform much more closely to international experience.

As discussed earlier in this paper, there are several studies that use the international data of Summers and Heston to examine the differences between economies that have experienced rapid growth and those that have not. Mankiw highlights three problems that affect the entire literature of cross-sectional analysis. The first problem is simultaneity which is the most obvious problem with cross-country growth regressions. This means that the right hand side variables are jointly determined with the growth rate and they are not exogenous. There is a strong, positive correlation between investment and growth and a negative correlation between population and growth. For investment, this implies that high investment causes high growth, high growth causes high investment, or some third variable causes both high investment and high growth.

Cho (1996) finds that two of the most widely used control variables in conditional convergence regressions, the saving rate and the population growth rate do not appear to be exogenous with respect to growth. A negative bias in the regression coefficients is caused by the endogeneity of the control variables. He presents evidence for the endogeneity of the saving rate and the population growth and provides an alternative interpretation that contrasts with conditional convergence.

The second problem is multicollinearity which refers to the strong correlation between the explanatory variables. The regression of growth rates on a group of variables that exhibit substantial multicollinearity causes the differing measurement errors in right hand side variables. This means that countries having a higher initial per capita income, also have higher rates of investment, higher enrollments in primary and secondary schools, and lower rates of population growth.

A Low degree of freedom is the third problem. There are only about one hundred countries that could be used to run a cross-country regression, while there are so many questions asked in economic growth. Therefore, the results of the study are contingent upon what variables the study chooses.

The endogenous growth literature has illustrated how to model technological progress as an endogenous process, while it is exogenous in the neoclassical growth model. Endogenous growth models provide an explanation of worldwide advances in knowledge. However, the neoclassical growth models take worldwide technological advances as given and offer an explanation of international differences. The neoclassical growth model predicts convergence, while the simple endogenous growth model[3] does not. Mankiw notes that the data seems to confirm the endogenous growth model since large samples of countries exhibit little evidence of convergence. However, the neoclassical model predicts conditional convergence consistent with data by allowing

[3] Y=AK is the simplest example of endogenous growth model.

different countries to have different steady states. Moreover, conditional convergence is consistent with more complicated endogenous growth models that show some form of transitional dynamics. Therefore, cross country regressions cannot distinguish among them.

Evans and Karras (1996) refer to the approach of estimating the cross sectional relationship between growth and the initial level of per capita output, as the conventional approach. They show that the conventional approach is valid only under incredible assumptions. These assumptions are as follows: the economies must have identical first order autoregressive dynamic structures. Also, all permanent cross economy differences have to be completely controlled for. They develop a different approach that is valid under less restrictive assumptions. They find convergence among 48 US states and also 54 countries which is the basic implication of neoclassical growth models. The common assumptions made in cross sectional studies such as that of identical economies except for initial conditions and stochastic disturbances are seriously inadequate and deficient. Nevertheless, their alternative approach reaches the same conclusion as the conventional approach.

As discussed before, MRW claim that the neoclassical growth model can be justified by including human capital in the regression. Islam argues that ignoring the heterogeneity of countries causes inconsistencies. In the next section, I discuss dynamic panel estimation approaches that are designed to remove the inconsistencies of cross sectional regressions.

4. Dynamic panel data approach

4.1. Panel data approach:

The cross-country studies of convergence based on a single cross country regression impose the assumption of an identical aggregate production function for all countries. Islam (1995) implements a panel data approach to take into account the differences across countries in the form of unobservable individual country effects.

Islam starts by investigating how the results of Mankiw, Romer and Weil (1992) change when applying a panel data approach. The regression used in the study of convergence is modified into a dynamic panel data model by including individual country-fixed effects. In the cross-country framework, unmeasurable or unobservable differences in technologies and preferences are not allowed for and the panel data approach can, in principle, overcome this problem.

4.1.1. Model

Islam asserts that the usefulness of a panel data approach can be demonstrated using the framework of MRW. As discussed before MRW substituted $\ln(A_0)=a+\varepsilon$ into the steady state per capita income equation in order to derive specification (1). At this stage, MRW provided several reasons why ε might be independent of population growth and the saving rate to allow for a valid OLS regression. The assumption of isoelastic preferences presents the additional restriction, in the view of Islam, since ε is likely to be correlated with the saving rate and population growth. In this case OLS is not valid and an instrumental variables approach must be used. Islam suggests that a panel data approach provides a better way to control for this technology shift term ε.

The out of steady state equation is derived by approximating around the steady state, although in this case human capital is not taken into account. The following equation for income per effective labor, $\hat{y} = \frac{Y}{AL}$, may be derived:

$$\ln(\hat{y}_{t1}) - \ln(\hat{y}_{t2}) = \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}\ln(s) - \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}\ln(n + g + \delta) - \left(1 - e^{-\lambda\tau}\right)\ln(\hat{y}_{t1}) \qquad (6)$$

where in MRW, t_1=1960 and t_2=1985 and τ=t_2-t_1. By reformulating the equation in terms of income per capita and making some small changes, we get:

$$\ln(y_{t2}) = \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}\ln(s) - \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}\ln(n + g + \delta) - \left(1 - e^{-\lambda\tau}\right)\ln(y_{t1}) + \left(1 - e^{-\lambda\tau}\right)\ln(A_0) + g(t_2 - e^{-\lambda\tau}t_1) \qquad (7)$$

The above equation includes a time invariant individual effect and represents a dynamic panel data model. $\left(1 - e^{-\lambda\tau}\right)\ln(A_0)$ represents the time-invariant individual country-effect term. Islam uses the following conventional notation from the panel data literature:

$$y_{it} = \gamma y_{i,t-1} + \sum_{j=1}^{2}\beta_j x_{it}^{j} + \eta_t + \mu_j + \upsilon_{it} \qquad (8)$$

where:

$$y_{it} = \ln(y_{t2})$$

$$y_{i,t-1} = \ln(y_{t1})$$

$$\gamma = e^{-\lambda\tau}$$

$$\beta_1 = \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}$$

$$\beta_2 = -\left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}$$

$$x_{it}^{1} = \ln(s)$$

$$x_{it}^{2} = \ln(n + g + \delta)$$

$$\mu_j = \left(1 - e^{-\lambda\tau}\right)\ln(A_0)$$

$$\eta_t = g(t_2 - e^{-\lambda\tau}t_1)$$

and υ_{it} represents the transitory error term.

This equation is estimated across countries over several short time periods, whereas the entire period of (1960-1985) was used in the single cross section. Assuming constant values for s and n is more realistic over shorter periods. The equation is approximated around the steady state and represents the dynamics toward the steady state.

4.1. 2. Method, data and results:

Islam uses the data sample of Summers and Heston to construct the variables. Exactly the same sample of countries as in MRW is used to make that comparison possible. Islam divides the total period into several shorter time spans. The appropriate length of such time spans is an important issue. Islam argues that 5 years intervals are appropriate time spans for studying growth convergence. First, Islam exactly replicates the work of MRW, and he gets the same results, i.e. a very slow rate of convergence and high estimates of α. He estimates the pooled regression on the basis of five year spans instead of a single cross section regression. The results of the pooled regression were quite close to their first regression. Thus, considering the growth process over 5 year intervals does not modify the results. He finds very high estimates of the elasticity of output with respect to physical capital and very low estimates of the rate of convergence. Therefore, he moves to panel estimation.

Islam considers two methods for the estimation of panel data models with individual effects. One of them is the Least Squares with Dummy variables (LSDV) estimator that is based on the fixed effect assumption. The other one is the Minimum Distance (MD) estimator proposed by Chamberlin (1982,1983).

The MD estimator accounts for the correlated nature of the individual effect term. In this method, μ_i is specifying as a function of the variables that seems to be correlated with it. Therefore, the MD estimator does not eliminate the individual effect by differencing the equation but it incorporates the correlation in the estimation. By implementing the MD estimator, the new equation is given by:

$$y_{it} = \gamma y_{i,t-1} + \beta x_{it} + \eta_t + \mu_j + \upsilon_{it} \qquad (9)$$

where:

$$\beta = \left(1 - e^{-\lambda\tau}\right)\frac{\alpha}{1-\alpha}$$

$$x_{it} = \ln(S) - \ln(n + g + \delta)$$

The results of MD estimation in Islam show that the rates of convergences are indeed much higher for non-oil and intermediate samples and do not change very much for the OECD samples in comparison with the corresponding single cross section results. Moreover, the estimated elasticity of output with respect to physical capital is found to be lower and closer to their generally accepted values. One of the interesting results of this part of the paper is that Islam finds these results are very similar and close to the results of MRW when he includes human capital as an input in production.

The LSDV estimator assumes that the individual country effects are fixed in nature. The results of this estimation are found to be very similar to those of the MD estimation. Islam concludes that the panel data approach leads to two acceptable changes in results: a higher convergence rate and a lower elasticity of physical capital. The statistical source of these changes is attributed to the correction of an omitted variables bias. The A_0 term in the single cross section regression is an unmeasurable and unobservable term that is correlated with the included explanatory variables and causes the biased estimation of the coefficients on these explanatory variables. The differences from the cross country regression are not only a result of the differences in n and g but also because of the differences in $\ln(A_0)$, which could represent initial technology, institutions, culture geography, etc. The results of the panel data approach shows that these differences are important enough to have significant effects on the convergence results.

In addition, Islam includes human capital in his analysis to investigate any changes to these results and the robustness of his estimation. The variable HUMAN from Barro and Lee (1993) is used to construct a human capital variable. HUMAN includes schooling at all levels of primary, secondary and higher education and also gives a direct measure of the stock of human capital. The equation is estimated as a single cross section regression, a pooled regression, and a panel regression. The single cross section regression with human capital yields higher rates of convergence and lower rates of α than without human capital variable. But the human capital coefficients are not significant in the OECD and intermediate countries samples. The pooled regression results are very different. In all three samples the estimated coefficients on human capital are not significant and the estimated values of α increase and are very similar to those obtained from a single cross section regression without human capital. The results of panel regression are very similar to the panel results without including human capital. These results are obtained since in two of the three samples the human capital variable is not significant and for all three samples the coefficients show up with negative signs (wrong sign). Islam concludes that the main properties of the panel estimation are robust to the inclusion of human capital in the regression.

In summary, Islam finds a higher rate of conditional convergence and a lower elasticity of output with respect to capital than in the single cross country regression. The omitted variable bias involved with the single cross section regression is (at least partly) corrected by the panel data approach, since the significance of cross-country differences in the aggregate production function are highlighted.

4.2. Generalized method of moments

The differenced and system GMM estimators are designed for short, wide panels and to fit linear models with one dynamic dependent variable, additional controls, and fixed effects. Differenced GMM estimates the model after first differencing the data in order to eliminate the fixed effects. System GMM augments differenced GMM by estimating simultaneously in differences and levels. In other words, the system GMM estimator combines moment conditions for the model in first differences with moment conditions for the model in levels.

The First differenced model was originally developed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991). This model was first used in the growth literature in the important contribution of Caselli, Esquivel and Lefort (1996). It is documented that estimators of this model have very poor finite sample features because the instruments are weak predicators of the endogenous changes. Blundell and Bond (1998) propose the use of extra moment conditions as proposed by Arellano and Bover (1995). The Mont Carlo studies undertaken by Blundell and Bond (1998) and Blundell, Bond, and Windmeijer (2000) show that the resulting system GMM estimates have much better finite sample properties in terms of bias and root mean squared error. The system

GMM is introduced into the empirical growth literature by Bond, Hoeffler and Temple (2001) by using country level panel data.

4.2.1. Differenced GMM:

The vast literature on cross country and cross regional studies of convergence has reached a broad consensus on a specific issue of convergence. In particular, the work of Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) have shown that countries converge to their steady state level of per capita output at a rate of approximately 2 percent while, the observations show that each year convergence is more than 2 percent. Therefore, the estimation procedure of cross country growth in the earlier empirical work discussed in this literature review is an inconsistent procedure, though they have shown the existence of convergence. Caselli, Esquivel and Lefort (CEL) (1996) present an alternative, consistent estimate of convergence.

Two sources of inconsistency are pointed out by CEL at their work. All the estimates discussed in this review so far are plagued by at least one of them. First, the technological and other differences across economies that give rise to an omitted variable bias are assumed to be uncorrelated with the other right side variables. Second, the explanatory variables should be expected to be endogenous. CEL try to solve these inconsistencies by using the panel data, general methods of moment's estimators.

The typical cross country study specifies economic growth as a function of per capita GDP in the first year, a country specific effect (η_i), and a vector of determinants of economic growth (w_{ti}). The variables in $w_{i,t}$ and η_i are proxies for the long run level of income that countries are converging to. The vector of $w_{i,t}$ consists of different variables such as measures of investment in physical and human capital, indicators of the quality and size of the government and many other covariates that have been included to determine the growth regression. The country-specific effect captures other variables that $w_{i,t}$ does not control for, such as differences in technology which are unobservable, and treats them as individual fixed-effects.

The cross sectional regression assumes that the individual effect is uncorrelated with the other right hand side variables. In the dynamic panel data model, this assumption is violated. Thus, there is a downward bias in the estimated convergence rate. The second issue in these works is endogeneity. It is reasonable to think that the rate of investment in physical capital is simultaneously determined with the rate of growth. Also, the rate of population is likely to be affected by the rate of economic growth.

The panel data approach tries to solve the problem arising in the cross section regression. On the issue of endogeneity, Barro and Lee (1994), and Barro and Sala-i-Martin(1995) divide the periods into two subperiods, and stack the two cross sections for the two subperiods. Then they apply a GLS estimator to deal with serial correlation, instrumenting the endogenous variables with their lagged values. This solution is consistent only under the assumption of a random individual effect that is correlated over time but not with other regressors. Thus, the correlation between the error term and the right hand side variables are induced by the GLS estimator and inconsistency arises.

There are some other panel data approach papers that address the question of correlated individual effects. The work of Islam (1995), Loayza (1994) are in this category. Since they have ignored endogeneity, their results may also be inconsistent.

Model and results:

The Generalized method of moment (GMM) estimator can simultaneously address the issues of endogeneity and correlated individual effects. CEL use the GMM estimator by Holtz-Eakin, Newely, and Rosen (1998), and Arellano and Bond (1991). All the linear moment restrictions implied by a dynamic panel data model are used by this GMM estimator. The general idea is following. First, the growth regression is rewritten as a dynamic model in the level of per capita GDP. Second, in order to eliminate the individual effects, first differences are taken. This step removes the omitted variable bias. Third, using lagged values of all right side variables as instruments, under the assumption that the time varying disturbances in original levels equations are not serially correlated. The last step removes the inconsistency arising from the endogeneity of the explanatory variables. The consistency of the GMM framework critically depends on the identifying assumption that the lagged values of income and other explanatory variables are valid instruments in the growth regression.

The benchmark model of MRW is used to revisit the empirical case of the Solow model in CEL. First, the consistent estimate of the Solow model is compared to other estimates that have the problem of omitted variable and/or endogeneity bias. Second, their estimate is used to figure out whether the Solow model is consistent with the data. They focus on the same time period span used in previous studies of the Solow model and use the five year data interval. The restricted and unrestricted Solow model specification is estimated by the method of MRW, pooled OLS regression, panel data according to the work of Knight, Loayza, and Villaneuvu(1993) (KLV) and the GMM estimator. MRW estimate a very low speed of convergence. The estimates of the convergence rate in the pooled OLS regression is very close to the MRW results. This shows that breaking the twenty five year interval into shorter time interval does not impact the results. The implied convergence coefficient according to the panel approach involves a correct treatment of the correlated individual effect and delivers a higher estimated value. The GMM estimates capture the role of endogeneity and correlated individual effects simultaneously. The comparison shows that the country specific effect is important but it is not the end of the story. In other words, the correction for endogeneity gives intermediate results between the MRW estimates and GMM.

As discussed in the previous section, MRW reject the textbook Solow model since the speed of convergence is very low and the capital share is too high. CEL reject the textbook Solow model because the speed of convergence in their study is too high. In KLV the estimated capital share is one third which is consistent with the Solow model. Thus, the intermediate result is obtained by capturing the individual effect with strictly exogenous regressors. After rejecting the Solow model, MRW estimate an augmented Solow model by including the human capital in the production function. They obtain reasonable results from the augmented model. CEL reject the model because of the high value of convergence rate, so including human capital seems does not work for their model.

The more general specification is used in the work of CEL since the specific functional form associated with the Solow neoclassical growth model is rejected. They regress the rate of growth of real per capita GDP on two sets of variables. First, only the initial level of GDP per capita is considered. Second, a set of control variables that captures differences in the steady state across countries is included.

The specification is a log-linearization around the steady state of the form:

$$\ln(\hat{y}_t) - \ln(\hat{y}_0) = -\left(1 - e^{-\lambda t}\right)\ln(\hat{y}_0) + \left(1 - e^{-\lambda t}\right)\ln(\hat{y}^*) \qquad (10)$$

where $\hat{y}_t$ is GDP per effective worker at time t, $\hat{y}^*$is its steady state value, and λ is the convergence rate. The panel including five year periods from 1960 to 1985 for the Barro and Lee (1994) sample of ninety seven countries is used. State variables in each regression are as follows. The initial level of per capita GDP, the average numbers of years of male and female secondary schooling, and the logarithm of an index of life expectancy are state variables. The control variables are the investment ratio, the government consumption ratio, and the number of revolutions. The results of estimation show that rate of convergence is approximately 10 percent per year. International differences in per capita income levels are explained mainly by differences in technology. They find that the open economy version of neoclassical growth model is supported by the data. Including the human capital as an input in the aggregate production function is not supported by the evidence.

In summary, two sources of inconsistency have a striking effect on standard regression results. Hence, they have shown that eliminating endogeneity and omitted variable biases raises the estimated rate of convergence from 2 percent to about 10 percent.

4.2.2. System GMM:

Bond, Hoeffler and Temple (BHT) (2001) point out a serious difficulty with the first differenced GMM method. The first difference GMM estimator is poorly behaved when the time series are persistent and the number of time series observations is small. Under these conditions, lagged levels of the variables are week instruments for subsequent first differences. For most countries GDP is a highly persistent series, and most growth applications consider a small number of time periods, based on five years interval. Thus above properties are present in empirical growth models and lead the first difference GMM estimator to present difficulties. BHT illustrate the problems implied by the first difference GMM estimator and propose the use of the system GMM estimator suggested by Arellano and Bover (1995) and Blundell and Bond (1998) to achieve more plausible results.

BHT show that the first difference GMM estimator has poor finite sample properties since the lagged levels of the series are only weekly correlated with subsequent first differences. Therefore, the available instruments for first differenced equations are weak. Bundell and Bond (1998) find that the first differenced GMM estimator may be subject to a large downward finite sample bias when there is a small number of a time period. Therefore, inclusions of the explanatory variables, current or lagged value of these variables, other than the lagged dependent variable improve the behavior of the first differenced GMM estimator.

The system GMM estimator is the combination of the standard set of equations in first differences with lagged levels as instruments, and an additional set of equations in levels with lagged first differences as instruments. The derivation of the system GMM is presented in the work of Blundell and Bond (1998). They compare the first differenced GMM and system GMM estimators using Monte Carlo simulations to show that the autoregressive parameter is weakly identified in the case of the first differenced equations. Blundell, Bond and Windmeijer (2000) estimate the model with a lagged dependent variable and additional right hand side variables. Their model is very similar to the typical equations estimated in the empirical growth literature.

Model and results:

BHT estimate the Solow growth model using system GMM. The following growth equation is estimated:

$$\Delta y_{it} = \gamma_t + (\alpha - 1)y_{i,t-1} + x_{it}\beta + \eta_i + v_{it} \qquad (11)$$

where Δy_{it} is the log difference in per capita GDP over five year interval, $y_{i,t-1}$ is the logarithm of per capita GDP at the start of the that interval, x_{it} is a vector of explanatory variables include the logarithm of the population growth (n_{it}) plus 0.05 (the sum of a common exogenous rate of technical change (g) and a common depreciation rete (δ)), and the logarithm of the investment rate (s_{it}). the logarithm of the secondary-school enrollment rate to capture the human capital effect in the augmented Solow model. η_i respresents unobserved country specific effects reflected in differences in the initial level of efficiency, and γ_t is a vector of period specific intercepts that captures productivity changes.

The above model also can be written as follow:

$$y_{it} = \gamma_t + \alpha y_{i,t-1} + \beta x_{i,t} + \eta_i + v_t$$

Therefore, the first difference would be:

$$\Delta y_{it} = \gamma_t - \gamma_{t-1} + \alpha \Delta y_{i,t-1} + \Delta x_{it}\beta + \Delta v_{it}$$

The same data set used by CEL is used in order to compare the results of system GMM and other findings. They present the results using basic OLS, a within groups estimator, the first differenced GMM estimator, and system GMM. In the first differenced and system GMM estimates, investment rates and population growth rates are treated as endogenous variables. Instruments used for differenced GMM estimator are $\ln(y_{i,t-2})$, $\ln(s_{i,t-2})$, and $\ln(n_{i,t-2} + g + \delta)$. Additional instruments used for the levels equations in system GMM are $\Delta \ln(y_{i,t-1})$, $\Delta \ln(s_{i,t-1})$ and $\Delta \ln(n_{i,t-1}, g + \delta)$.

The estimated coefficient on initial income in the first differenced GMM results are less than the estimated coefficient in the within group estimates and greater than the estimated coefficient of OLS regression. BHTs results indicate finite sample biases in the GMM estimator by comparing the first differences GMM results to OLS and within group results. The OLS estimation gives an upwardly biased estimate in the presence of individual specific effects, while within groups gives a downwardly biased estimated coefficient in short panels. Therefore, the consistent estimate is expected to lie in between the OLS levels and Within groups estimates. Since the first difference GMM estimates is below the Within Groups estimate, it could be concluded that the GMM estimate is also biased downwards perhaps because of weak instruments.

The results of system GMM shows that the coefficient on initial income lies above the within group estimates and below the OLS level estimate. The results show that a serious finite sample bias problem caused by weak instruments in the first differenced GMM estimator could be addressed using system GMM. The results imply a rate of convergence of around 2% a year, which is similar to the standard cross section results. Hence, they get a rate of convergence considerably slower than what found by CEL. Moreover, they find that human capital can be omitted from the specification of the model.

In summary, the low convergence rate in the region of 2% to 4% a year is confirmed by system GMM. These findings show that there is a great deal of uncertainty in measuring convergence rates. BHT try to highlight the problems of first differenced GMM estimation in estimating empirical growth models rather than presenting definitive estimates of convergence.

4.3. Some more GMM studies:

Bun and Windmeijer (2010) highlight some characteristics of the country level panel data model that leads to a weak instrument problem for system GMM estimator. These characteristics are as follows: The country level panel data are determined by highly persistent series and a very small number of countries and time periods. Moreover, it is expected that the variance of the country effect is very high relative to the variance of the transitory shock.

A measure of the information content of the instruments for a simple cross section linear instrumental variable model is called a *concentration parameter*. Bun and Windmeijer calculate the expected concentration parameter for the level and differenced models in AR(1) panel data model. They show that these two parameters are identical when constant unobservable heterogeneity term is equal to the variance of the idiosyncratic shocks. These are exactly the conditions under which most Mont Carlo results show the superiority of the system GMM estimator relative to the difference GMM estimator. Equal expectation of the concentration parameters exhibit that there is a weak instrument problem in the level model when there is a persistent time series. Furthermore, they show that in the persistent series, the bias of the OLS estimator in level models is much smaller than the bias of the OLS estimator in first differenced model.

Hauk and Wacziarg (2009) use simulation methods to measure the bias properties of several estimators commonly used in the empirical growth literature. They show that the inclusion of fixed effects causes the speed of conditional convergence be much higher than the 2 percent obtained in cross sectional studies. Therefore, the fixed effect estimators that are used to control for time invariant cross country heterogeneity, as well as the Arellano-Bond (first differenced GMM) estimator, overstate the speed of convergence under the assumptions concerning the type and extent of measurement error. The random effect estimators tend to overstate the speed of convergence but not with as much intensity as the fixed effect estimator. The instrumental variables model of the Blundell-Bond (system GMM) GMM estimator tends to correct the deficiencies of the fixed effect and the Arellano-Bond estimators. They show that simple OLS provides a closer estimate of the speed of convergence, while it overestimates the magnitude of steady state determinants.

5. Spatial growth model:

5.1. Studies of growth model with spatial effects:

Several theoretical and empirical studies argue that regions are not independent in addition to not being homogeneous. Rey and Montouri (1999,p.144) argue that “Despite the fact that theoretical mechanisms of technology diffusion, factor mobility and transfer payments that are argued to drive the regional convergence phenomenon have explicit geographical components, the role of spatial effects in regional studies has been virtually ignored.” Rey and Montouri are amongst the first to include spatial effects in empirical growth models to check for absolute β-convergence under spatial heterogeneity and spatial interdependence. Several studies such as Amstrong (1995), Bernat (1996), Rey and Montouri (1999), Fingleton (2001), and Rey and Janikas (2005) show that the spatial specification depends on the set of regions, time period, specification, etc.

Badinger, Muller and Tondl (2004) propose a model of an underlying dynamic panel with spatial dependencies. They use a two step estimation procedure with the purpose of estimating a dynamic spatial panel data model for European regions. Moreover, they use standard GMM estimators to make a conclusion on convergence. They conclude that considering spatial dependencies changes the estimated speed of convergence significantly and ignoring it may lead to seriously misleading results. First differenced GMM performs relatively poor in their study, therefore, they decide to use the system GMM. The results in their study indicate that the speed of convergence of Europe region amounts to some 7 percent.

Fingleton, and Lopez-Bazo (2006) assert that ignoring the effect of spatial locations in the growth model leads to biased results and hence misleading conclusions. They assume that technological diffusion and pecuniary externalities cause externalities across regions in long run growth. They base their study on a structural growth model including externalities across economies. The appropriate spatial econometric tools are applied to test for their presence and estimate their magnitude in the real world. This approach is also used in Fingleton (2001 and 2004).

Lesage and Fischer (2008) illustrate that the steady state level of income depends on own regional and neighboring region characteristics, the spatial effect of the region and the strength of spatial dependence. Therefore, they argue that the growth rate should take into account spatial dependences, own and neighboring region characteristics by using a weighting matrix and spatial regression model specification. Selecting the appropriate spatial weighting matrix and explanatory variables are important in the analysis of growth empirics.

Fischer (2010) considers the role of cross regional technological knowledge spillovers in economic growth by focusing on the augmented Solow model of MRW. He extends the MRW model by taking into account technological interdependence among the economies. He shifts his attention from countries to regions as a more appropriate arena for analyzing growth processes. A system of 198 regions across 22 European countries over the period 1995 to 2004 is used in this paper to test their model.

In the following subsection, one of the most recent spatial dynamic panel data model by Yu and Lee (2012) will be discussed.

5.2. Spatial dynamic panel data model:

The neoclassical growth model used in most of the empirical growth literature assumes that economies are independent. Therefore, the transmission of technological advances from one economy to another are ignored, potentially leading to unreliable statistical inferences. Hence, the assumption of a closed economy might not be valid. Yu and Lee (2012) consider a spatial panel data model to study convergence across open economies. They use an augmented Solow model and include the spatial interdependence among US states due to technological spillovers. They take Islam (1995) as a starting point and examine how the estimated rate of convergence changes with the adoption of a spatial dynamic panel data (SDPD) approach. They argue that by using a SDPD model with regional fixed effects, the omitted variable bias in cross sectional regressions and the omitted variable bias in the dynamic panel data regression can be avoided.

As we mentioned earlier in this paper, Barro and Sala-i-Martin obtain evidence of convergence for the 48 contiguous US states by assuming that preferences and technologies are identical across economies. However, Islam estimates a higher rate of convergence and a lower rate of the elasticity of output with respect to capital by allowing for differences in preferences and technologies across countries. Islam got these results by assuming cross-sectional independence, which could be acceptable for studying the cross countries convergence. However, this is likely to be unrealistic in studying convergence amongst US states. Technology, goods, capital and labor can easily be transferred from one region to another one. Thus, allowing for the possibility of interdependence among US states is necessary when estimating the dynamic panel data model in order to avoid the potential for omitted variable bias.

5.2.1. Model:

The Solow model is augmented by including spatial dependence and introducing technological spillovers. The growth rates of labor and technological advance are assumed to be constant in the neoclassical model, while they allow technological advances in one state to have spillover effects on others.

The level of technology in region i (A_{it}) is specified as:

$$A_{it} = A_{i0} e^{gt} \prod_{j \neq i}^{n} A_{jt}^{\emptyset w ij}$$

This equation shows that A_{it} is determined by its own initial level A_{i0} and its exogenous growth rate g, and its neighbors A_{jt} which may spillover to region i. The magnitude of the spillover effect is measured by Φ and w_{ij} specifying the neighboring structure to capture how much technology is transmitted from region *j* to region *i*. consequently the growth rate of technology in region *i* is given by:

$$\frac{\dot{A}_{it}}{A_{it}} = \frac{g}{1 - \emptyset}$$

From the dynamics of capital, the steady state level of capital is:

$$\hat{k}i* = \left(\frac{s_i}{\mathrm{n} + \mathrm{g}/(1-\emptyset) + \delta}\right)^{1/(1-\alpha)}$$

where, s_i is the saving rate and δ is the depreciation rate.

These equations show that with positive spillovers *Φ*, the overall growth rate of technology increases. Also a positive value of *Φ* decreases the steady state value of capital per effective worker. The speed of convergence under the SPDP approach is given by:

$$\lambda = (1-\alpha)(\mathrm{n} + \frac{\mathrm{g}}{1-\emptyset} + \delta)$$

The convergence rate under the SPDP is higher than the MRW rate of convergence$(1-\alpha)(\mathrm{n}+\mathrm{g}+\delta)$, since the technological growth rate is increased due to technological spillovers. Compared to Islam's specification in equation (10) Yu and Lee add extra terms to capture the dependence among economies due to technological spillovers. The estimation equation in Yu and Lee is:

$$lny_t = \emptyset W_n lny_t + \gamma lny_{t-1} + \rho W_n lny_{t-1} + c_n + \eta_t I_n + V_{nt} \quad (12)$$

where

$$\gamma = e^{-\lambda}$$

$$\rho = -\emptyset e^{-\lambda}$$

$$c_n = \left(1 - e^{-\lambda}\right)(\ln A_0 + \frac{\alpha}{1-\alpha} ln \frac{S}{\mathrm{n} + \frac{\mathrm{g}}{1-\emptyset} + \delta} - \frac{\alpha\emptyset}{1-\alpha} W_n \frac{S}{\mathrm{n} + \frac{\mathrm{g}}{1-\emptyset} + \delta})$$

$$\eta_t = g.(t_2 - e^{-\lambda} t_1)$$

Here W_n is an $n \times n$ matrix with w_{ij} being its (i,j) entry and I_n is an $n \times 1$ vector of ones. W_n captures the cross sectional dependence among individuals. V_{nt} is a vector of transitory error terms. The extra terms that capture the dependence among economies are

$\emptyset W_n lny_t$ and $\rho W_n lny_{t-1}$. As a convention $W_n lny_t$ is called the spatial lag, $lny_{t-1}$is a time lag , and $W_n lny_{t-1}$is a so-called spatial time lag (Tao and Yu (2012)).

5.2.2. Results:

They use annual data on nominal state personal income (SPI) for 48 contiguous states since 1929 from the Bureau of Economic Analysis (BEA). To capture the spillovers effect, a spatial weight matrix is used. According to previous empirical evidence, (Griliches (1992) and Keller (2002)) knowledge spillovers are geographically bounded and fade rapidly across the geographic space. They use a weighting matrix such that if two states share a common border it has an element of 1 and 0 otherwise. Hence a time-invariant spatial weighting matrix constructed from the physical distance between economies is used.In this study, β-convergence is used, which emphasizes the relationship between the initial income level and the subsequent growth rate. They use Quasi maximum likelihood estimation (QMLE) to estimate the spatial dynamic panel data equation. To do this, several methods are applied and explained in their paper. Moreover, in order to provide some evidence on the performance of different estimation methods, the SDPD estimator is simulated using a Monet Carlo simulation.

Yu and Lee present their empirical results for cross sections and panel data separately. First, they estimate a single cross sectional regression, a pooled regression with 5 year intervals and a pooled regression with 4 years intervals, each with and without spatial effects and lagged spatial effects. All these results are shown in three tables in their paper. They run the cross sectional regressions for different periods of: 1930-1965, 1965-2005, 1930-2005 and 1946-2005. The results without spatial effects for both the single cross-sectional regression and pooled regression are similar to those of Barro and Sala-i-Martin (1992) that we discussed earlier. The similar results for the single cross section and pooled regressions are obtained when including spatial effect, and spatial effect is not significant in these two regressions.

They argue that the insignificant spatial effect might be due to the omitted individual effect as well as omitted lagged spatial effect. Hence, they expect that adding the lagged spatial effects may make them significant. The results of cross section regression when including both contemporary and lagged spatial effects have shown the significant spatial interaction terms. They determine that the speed of convergence in the cross sectional regression compared to the panel data regression is very slow because there are no controls for individual fixed effects. Therefore, the convergence in cross sectional data should be interpreted as absolute convergence. The results of dynamic panel estimation are similar to the results of Isalm (1995) discussed earlier in this. After that, they have used the SDPD and used several methods to estimate the equation. A higher rate of convergence is obtained when they include the spatial effects, which is consistent with the theory discussed earlier. Also, they find that both contemporary and lagged spatial effects are significant. Finally, when they change their weighting matrix so that it takes into account more neighbors for each state, they get the same results for the convergence rate.

To sum up, Yu and Lee (2012) use the spatial dynamic panel data model to avoid an omitted variable bias associated with spillovers which is possible for both cross sectional and standard panel estimation. Their results suggest much higher speed of convergence compare to Barro and Sala-i Martin (1992) and Islam(1995) studies and also are consistent with the theory.

5.3 Comments and criticism:

Bouayad-Agha and Vedrine (2010) include spatial considerations in dynamic panel data models. They apply GMM in a spatial context in order to correct the endogeneity of the spatially lagged dependent variable and other potentially endogenous explanatory variables. They suggest an estimation strategy that considers both the dynamic specification and the spatial dimension of the panel in order to investigate regional conditional convergence. They concentrate on studying strategies to estimate spatial dynamic panels using GMM. Bouayad-Agha and Vedrine rely on dynamic panel GMM estimations which control for endogeneity and spatial dependence problems. To do this they extend the moment restrictions of Arellano and Bond's estimator to a spatial autoregressive dynamic panel. They find empirical evidence of conditional convergence amongst European regions allowing for the spatial dimension of regional growth. The results show that convergence is significantly influenced by spatial disparities between regions. Furthermore, technological spillovers play a key role in the convergence pattern of European regions.

Tao and Yu (2012) try to provide a simple theoretical justification for the necessity of including the spatial time lag in empirical specifications. They indicate that when both time lag and spatial lag have positive coefficients, the spatial time lag term has negative coefficients. Tao and Yu suggests by Monte Carlo simulation that omitting a relevant spatial time lag term leads to significant biases in regression estimates, whereas including an irrelevant spatial time lag term only can result in a little loss of efficiency. They therefore conclude that if the true model has a spatial time lag which is ignored in the specification, the model might face the problem of omitted variable bias in parameter estimation. On the other hand, if the true model does not have spatial lag term, but it is included in the model, it only causes some efficiency loss. Therefore, including the spatial time lag is recommended to be included in the model.

Ho, Wang and Yu (2013) examine the international spillover effects of growth from one country to its trade partners with the Solow growth model. They apply a spatial dynamic panel data (SDPD) model to estimate the Solow growth model. Yu and Lee (2012), as mentioned before, use a time-invariant spatial weighting matrix which implicitly assumes that the relative dependence among different economies are constant over time, while Ho, Wang and Yu use a time-varying spatial weighting matrix. This weighting matrix incorporates the spillover effects influenced by trade volumes which are time varying. Their model avoids the omitted variable bias in the cross sectional regressions by including country and time fixed effects. Moreover, they allow for a couple of time-varying explanatory variables in the model to capture labor and capital in the Solow growth model, in contrast to Yu and Lee (2012). They estimate a higher rate of convergence with the inclusion of spatial terms in the growth model than without spatial effects. The results are consistent with the evidence reported in Yu and Lee (2012).

6. Conclusion:

One of the main questions asked in economic growth is whether relatively poor economies grow faster than rich economies? The issue of convergence is defined as a tendency of poor economies to grow more rapidly than rich economies. The neoclassical growth model predicts that each economy converges to its own steady state which is determined by its own population growth and saving rates. This notion of convergence is called conditional convergence. Many studies have run regressions of growth rates on initial income, and a set of other variables to control for determinants of the steady state. Mankiw, Romer and Weil argue that a simple expansion of Solow model which includes human capital accounts reasonably well for the observed pattern of growth.

Although, their work cast light on a number of issues, there are some noticeable problems with estimating growth regressions. The right hand side variables are likely to be endogenous and badly measured. Moreover, the assumption that they are uncorrelated with unobserved differences is not valid.

Therefore, more rigorous estimation methods have been applied, in order to address issues of endogeneity, measurement error and omitted variables. One outstanding way to address these problems was introduced by the work of Caselli, Esquivel and Lefort. They apply the first differenced generalized method of moments estimator to dynamic panel data models. First differenced GMM has important advantages over single cross section regression and other estimation methods for dynamic panel data models. First, estimators are not biased by any omitted variable since unobservable country specific or fixed effects are included in the model. Second, instrumental variables address endogeneity in the context of growth equation. Finally, instrumental variables allow consistent estimation in the presence of measurement error. However, there is a problem in using the first differenced GMM panel data estimator when the time series are persistent. The first differenced GMM estimator could be invalid because lagged levels of the series are only weak instruments for subsequent first differences. More acceptable estimates can be obtained by the system GMM estimator. System GMM uses lagged first differences of the variables as instruments with lagged of the variables. The validity of additional instruments shows that the system GMM approach is probably preferable in measuring economic growth convergence. However, it has been shown in several recent studies that although system GMM corrects some deficiencies of first differenced GMM , it still leads to some bias.

The non-spatial growth regression literature potentially ignores important spatial spillover effects that arise from changes in own region characteristics. There is a vast consensus that regional income growth rates show spatial dependence. In one of the most recent spatial growth models, introducing technological spillovers into the neoclassical growth model leads to a higher rate of convergence and shows spatial interaction in the model. Hence, recent studies illustrate that spatial dependence is an important factor in regional convergence and indicates more a plausible rate of convergence in region studies.

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