# Estimation of growth convergence using common correlated effects approaches

Jen-Chieh Cheng * Chang-Ching Lin †
Chien-Ho Wang‡

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**Abstract**

This paper reexamines the evidence on the conditional multiple convergence growth theory under cross country dependence. We extends Islam's (1995) dynamic panel data growth model to allow for cross country dependence and group-specific parameters by using the common correlated effects pooled (CCEP) by Pesaran (2006) and then utilitizing the threshold model by Hansen (1999, 2000). Empirical results indicate that (1) the dependence across countries are significant and (2) with controlling cross country dependence, the convergence rates estimated by CCEP method are faster than conventional results obtained from the Dummy Variable Least Square (DVLS) method. We also find that countries are clustered into two groups with distinct convergence dynamics, which is different from the conventional classifications in the literature of growth.

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*Keywords: Conditional convergence; Cross sectional correlation; Dynamic panel data; Multiple equilibria growth model; Threshold model.*

# 1 Introduction

The relationships between economic growth and its determinants have been studied extensively in economic literature. A large number of empirical studies have found that economic growth is related to initial income, population growth, investment and human capital. The economic growth can be generally divided into two parts: the growth to the steady state

*Research Assistant, Research center of humanities and social sciences, Academia Sinica.
†Institute of Economics, Academia Sinica, 115 NanKang Taipei Taiwan Republic of China, Email lincc@econ.sinica.edu.tw.
‡Department of Economics, National Taipei University, 3F36 Social science building, 151 University road, San Shia, Taipei county, 237, Taiwan Republic of China, Email wangchi3@mail.ntpu.edu.tw.

and dynamic transitional growth. It is possible that the transitional growth rates are persistent and large with the effect of technological diffusion between high developed countries. If the transitional growth rates are different and persistent in each countries, the convergence rates of global economy by conventional estimation method would be underestimated. Lee, Pesaran, and Smith (1997) consider that technology growth rates and speeds of convergence are heterogeneous across all countries. They find high convergence rates after controlling the heterogeneity in different countries. This result implies that countries converge to a steady state by very quick rate if the actual economic growth rates do not include the transitional growth rates. Moreover, there exists many common factors in global economy which can be divided into two types, observed and unobserved common factors. The observed common factors can be explained by regional free trade agreement or international organization like European Union and NAFTA (North American Free Trade Agreement), but there are many unobserved common factors like global greenhouse effect or oil crisis. In estimation of panel data, the spatial correlations and unobserved common factors in regression cause the cross-section dependence. When cross-section dependence and heterogeneity of technology growth appear in cross-country data sets, the conventional estimation and inference will be severely biased. For example, Pesaran and Tosetti (2007) show that the DVLS estimators are biased when spatial correlations and/or common factors exist in panel data.

We start the dynamic panel data model proposed by Islam (1995) based on Solow growth model with Cobb-Douglas production function. However, the parameter homogeneity assumptions in the conventional linear regression model may be too strong to get consistent estimator when we use the pooled estimation. In recent researches by Hansen (2000) and Masanjala and Papageorgiou (2004), they use the threshold methodology to split the countries and reject the linear model commonly used in studying cross-country growth behavior in favor of a multiple regime alternative in which different economies obey different linear models when grouped according to initial conditions. In this paper, we will also extend the estimation model flexible enough to control for both threshold effects and cross-section dependence by simultaneously utilizing the splitting methodology of Hansen (1999) and CCE method.

The role of human capital in economic growth could generate long-term sustained growth in recent initial growth literature proposed by Lucas (1988) and Romer (1990), but the neoclassical literatures evolved from Mankiw, Romer, and Weil (1992) describe human capital as an ordinary input. Human capital accumulations are unable to generate endogenous growth. They use the schooling years to evaluate the human capital. In literatures, schooling years data set of Barro and Lee (2001) is popularly used. In this research we use Barro and Lee human capital data with dynamic panel data to investigate the impact of human capital to economic growth.

The rest of the paper is organized as following. Section 2 derives the regression equations from the Solow growth model under Cobb-Douglas production technologies and introduce the Pesaran's approach, three tests for cross-section dependence and the panel threshold model proposed by Hansen. Section 3 explains the source of data and reports the test results for detecting the cross-section dependence. Section 4 presents and discusses the empirical results. The conclusion is in Section5.

# 2 Economic growth models

Consider Solow growth model with Cobb-Douglas production function.

$$Y = K^a H^b (AL)^{1-a-b}, 0 < a < 1, 0 < b < 1, a + b < 1, \quad (1)$$

where $Y$ is output, $K$ is the stock of real capital, $H$ is the stock of human capital, $A$ is the level of technology, and $L$ is labor. The level of technology and labor growth at constant rate $g$ and $n$, respectively such that as $A(t) = A(0)e^{gt}$ and $L(t) = L(0)e^{nt}$. The depreciate rate $\delta$ is constant. The real capital accumulation and the human capital accumulation equations are

$$\dot{K} = sY - \delta K \quad (2)$$

and

$$\dot{H} = s^h Y - \delta H, \quad (3)$$

where $\delta$ is the rate of depreciation, $s_k$ is the fraction of income invested in real capital, and $s_h$ is the fraction of income invested in human capital. We define that output per capita is $y = Y/L$. The logarithm of income per effect labor is

$$\ln(\frac{Y(t)}{A(t)L(t)}) = \ln(\frac{Y(t)}{L(t)}) - \ln A(0) - gt = \ln(y(t)) - \ln A(0) - gt, \quad (4)$$

Over any time interval $t_1$ to $t_2$, The logarithm of output per worker obeys

$$\ln(y(t_2)) = e^{-\lambda\tau} \ln(y(t_1)) + (1 - e^{-\lambda\tau})[\frac{a}{1-a-b} \ln(s) + \frac{b}{1-a-b} \ln(s^h)$$

$$-\frac{a+b}{1-a-b} \ln(n + g + \delta)] + (1 - e^{-\lambda\tau}) \ln A(0) + g(t_2 - e^{-\lambda\tau} t_1), \quad (5)$$

where $\tau$ is the time difference between $t_1$ and $t_2$[1]. Equation (5) represents a dynamic panel data model.

$$\ln(y_{it}) = \beta_i \ln(y_{i,t-\tau}) + \psi_i X_{it} + \alpha_i + g_i \eta_t + \varepsilon_{it}, \quad (6)$$

where $\ln(y_{it}) = \ln(y(t_2))$, $X_{it}$ is a vector of $\ln(s_{it})$, $\ln(n_{it} + g_i + \delta)$ and $\ln(s^h_{it})$, $\alpha_i = (1 - e^{-\lambda\tau}) \ln A_i(0)$, $\eta_t = t_2 - e^{-\lambda\tau} t_1$, and $\varepsilon_{it}$ is an independent disturbance. $\alpha_i$ captures any country-specific effect, such as initial endowments. $g_i\eta_t$ captures any common period-specific effect, such as general technical progress, on $i^{th}$ country. $A_i(0)$ term represents the difference among countries like technology and endowments. Islam (1995) first test the conditional $\beta$-convergence hypothesis with dynamic panel data regression. Islam (1995) use dummy variable least square (DVLS) method to estimate $\beta$, the average of $\beta_i$. Although dynamic panel data regression analyzes the growth convergence more precisely, omitting the cross section dependence will cause significant estimation bias in coefficient $\beta$ [2].

[1]About the details, please see Mankiw et. al. (1992) and Islam (1995).

[2]Because countries in the same area or same development level will have highly correlation by way of trade or capital movement, the error in $\beta$-convergence model may be correlated with countries.

A number of new growth models are based on multiple equilibria. Baumol (1986) find the economic growth rates will depend on the development condition of every county. The well-developed countries will show lower economic growth rates, and developing countries will have high growth rates. Durlauf and Johnson (1995) suggest that the cross-country growth model may exhibit multiple regimes according to initial conditions. Durlauf and Johnson (1995) reject the cross-country linear model specification which underlies most growth research and use regression tree methods to identify groups of countries. Hansen (2000) use threshold regression to estimate the convergence coefficients and threshold values. Although Durlauf and Johnson (1995) and Hansen (2000) consider nonlinear regression model to study growth convergence with multiple regimes, they only consider cross-section data. In this paper we try to use dynamic threshold panel data model with cross section dependence to analyze whether growth behavior obey a single-type Solow growth equation.

# 3 Econometric methodology

In this paragraph we describe our econometric procedure briefly. The first step of the analysis need to detect whether the economic growth data has cross section dependence. There are four kinds of cross section dependence tests considered in this paper: Breusch and Pagan (1980) Lagrange Multiplier (LM) test; Pesaran (2004) cross section dependence (CD) test; Pesaran and Tosetti (2007) the average of pair-wise cross section correlation coefficients and Pesaran, Ullah and Yamagata (2008) biased-adjusted Lagrange Multiplier ($LM_{adj}$) test. If all these tests accept cross section dependence existence, we can choose suitable econometric tool to obtain consistent estimators under cross section dependence.

When the data has cross section dependence, we consider two kinds of dynamic panel data regressions. First, we estimate the linear dynamic panel data model like Equation (6). We use cross-sectionally augmented regression proposed by Pesaran (2006) to get rid of $g_i\eta_t$

$$\ln(y_{it}) = \alpha_i + \beta \ln(y_{i,t-1}) + \psi_i X_{it} + c_i \overline{\ln(y)}_t + d_i \overline{\ln(y)}_{t-1} + \nu_i \bar{X}_t + \varepsilon_{it}, \tag{7}$$

where $\overline{\ln(y)}_t = 1/N \sum_{i=1}^N \ln(y_{it})$ and $\bar{X}_t = 1/N \sum_{i=1}^N X_{it}$. After the cross section dependence is eliminated, $\beta$ can be estimated by common correlated effects pooled (CCEP) method. We may compare CCEP estimator with traditional DVLS estimator.

Second, we will consider threshold model with cross section dependence like

$$\ln(y_{it}) = \begin{cases} \beta_1 \ln(y_{it-1}) + \mathbf{\Psi_{i1}} X_{it} + g_i\eta_{1t} + \varepsilon_{it}, & q_i \leq \gamma \\ \beta_2 \ln(y_{it-1}) + \mathbf{\Psi_{i2}} X_{it} + g_i\eta_{2t} + \varepsilon_{it}, & q_i > \gamma, \end{cases} \tag{8}$$

where $\eta_{jt}$, $j = 1, 2$ are unobserved common effect, $\lambda_i$ is factor loading and $q_i$ is threshold variable. There are three unknown parameters $\beta_1$, $\beta_2$ and $\gamma$ in Equation (8). When both threshold effects and cross-section dependence are present in the data of interest, we can also use the CCEP estimation proposed by Pesaran (2006) to eliminate cross section dependence and estimate $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ in Equation (8). But the consistency of CCEP estimators $\hat{\beta}_1$ and $\hat{\beta}_2$ will depend on threshold value $\gamma$. We must obtain consistent estimator $\hat{\gamma}$ in advance. The computationally convenient method to obtain CCEP estimators is concentrated Equation (8) conditional on $\gamma$. We split cross-section units into two groups according to $\gamma$. There are $N_1$ cross-section units under $q_i \leq \gamma$ and $N - N_1$ units with $q_i > \gamma$. When $q_i \leq \gamma$, we denote $\mathbf{z}_{it}^1 = (\ln(y_{it}), X_{it})'$ and the cross-section average of the individual-specific variables are $\bar{\mathbf{z}}_{wt}^1 = \sum_{i=1}^{N_1}(1/N_1)\mathbf{z}_{it}^1$. Let $\overline{\mathbf{M}}_{1w} \equiv \mathbf{I}_T - \overline{\mathbf{H}}_{1w}(\overline{\mathbf{H}}_{1w}'\overline{\mathbf{H}}_{1w})^{-1}\overline{\mathbf{H}}_{1w}'$ be the orthogonal matrix, where $\overline{\mathbf{H}}_{1w} = \overline{\mathbf{Z}}_{1w}$. $\overline{\mathbf{Z}}_{1w} = (\bar{\mathbf{z}}_{w1}^1, \bar{\mathbf{z}}_{w2}^1, \ldots, \bar{\mathbf{z}}_{wT}^1)'$ is the $T \times (k+1)$ matrix of observations on the cross-section averages. When $q_i \leq \gamma$, the CCEP estimator is

$$\hat{\beta}_1(\gamma) = \left(\sum_{i=1}^{N_1} w_{i1}\mathbf{X}_i'\overline{\mathbf{M}}_{1w}\mathbf{X}_i\right)^{-1} \sum_{i=1}^{N_1} w_{i1}\mathbf{X}_i'\overline{\mathbf{M}}_{1w}\mathbf{y}_i, \tag{9}$$

where $w_{i1} = 1/N_1$. The regression residuals under $q_i \leq \gamma$ are

$$\hat{\mathbf{e}}_{1i}(\gamma) = \overline{\mathbf{M}}_{1w}y_i - \hat{\boldsymbol{\beta}}_1(\gamma)'\overline{\mathbf{M}}_{1w}X_i. \tag{10}$$

The sum of square errors in regime $q_i \leq \gamma$ is

$$\mathbf{S}_1(\gamma) = \sum_{i=1}^{N_1} \hat{\mathbf{e}}_{1i}(\gamma)'\hat{\mathbf{e}}_{1i}(\gamma). \tag{11}$$

By the same way, we can estimate the $\boldsymbol{\beta}_2$ for those cross-section units with $q_i > \gamma$. When $q_i > \gamma$, we denote $\mathbf{z}_{it}^2 = (\ln(y_{it}), X_{it})'$ and $\bar{\mathbf{z}}_{wt}^2 = \sum_{i=1}^{N-N_1}(\frac{1}{N-N_1})\mathbf{z}_{it}^2$. Let $\overline{\mathbf{M}}_{2w} \equiv \mathbf{I}_T - \overline{\mathbf{H}}_{2w}(\overline{\mathbf{H}}_{2w}'\overline{\mathbf{H}}_{2w})^{-1}\overline{\mathbf{H}}_{2w}'$ be the transformation matrix, where $\overline{\mathbf{H}}_{2w} = \overline{\mathbf{Z}}_{2w}$. $\overline{\mathbf{Z}}_{2w} = (\bar{\mathbf{z}}_{w1}^2, \bar{\mathbf{z}}_{w2}^2, \ldots, \bar{\mathbf{z}}_{wT}^2)'$ is the $T \times (k+1)$ matrix of observations on the cross-section averages. When $q_i > \gamma$, the CCEP estimator can be expressed as

$$\hat{\beta}_2(\gamma) = \left(\sum_{i=1}^{N-N_1} w_{i2}X_i'\overline{\mathbf{M}}_{2w}X_i\right)^{-1} \sum_{i=1}^{N-N_1} w_{i2}X_i'\overline{\mathbf{M}}_{2w}\mathbf{y}_i, \tag{12}$$

where $w_{i2} = 1/(N - N_1)$. When $q_i \leq \gamma$, the vector of regression residuals is

$$\hat{\mathbf{e}}_{2i}(\gamma) = \overline{\mathbf{M}}_{2w}\mathbf{y}_i - \hat{\boldsymbol{\beta}}_{p2}(\gamma)'\overline{\mathbf{M}}_{2w}\mathbf{X}_i. \tag{13}$$

When $q_i > \gamma$, the sum of square errors is $\mathbf{S}_2(\gamma) = \sum_{i=1}^{N-N_1} \hat{\mathbf{e}}_{2i}(\gamma)'\hat{\mathbf{e}}_{2i}(\gamma)$. Using sum of square errors under different regimes, $\gamma$ can be estimated by following equation

$$\hat{\gamma} = \arg\min_{\gamma}(\mathbf{S}_1(\gamma) + \mathbf{S}_2(\gamma)). \tag{14}$$

After we obtain consistent estimator $\gamma$, the coefficient $\beta_1$ and $\beta_2$ can be estimated by way of Equation (9) and (12). When Equation (8) do not exist cross section dependence, CCEP estimator in Equation (9) and (12) will be degenerated as Hansen (1999) standard panel threshold estimator.

We also test whether the threshold effect is statistically significant by the bootstrap procedure analogical to Hansen (1999). We calculate the sum of squared error under null hypothesis $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_2$ and alternative hypothesis $\boldsymbol{\beta}_1 \neq \boldsymbol{\beta}_2$ and calculate the likelihood ratio test. We create a bootstrap sample from drawing the regression residuals under null hypothesis with replacement and calculate the bootstrap value of the likelihood ratio statistic. We repeat these procedures with 1000 times and calculate the p-value. We also try a double threshold model using the CCEP estimation and test the threshold effect.

# 4 Estimation and Results

## 4.1 Data and Sample

For $y_{it}$, $n_{it}$, $s_{it}$ and $s_{it}^h$ in Equation (6), we measure $y_{it}$ as the real GDP per capita (Constant Prices: Laspeyres), $n_{it}$ as the rate of population growth, $s_{it}$ as the average share of real investment in real GDP, and $s_{it}^h$ as the average years of schooling of the workforce — the population over ages 25. As Mankiw, Romer, and Weil (1992), we set $g_i + \delta = 0.05$ for all countries. The data of output, population, and investment come from Penn World Table Version 6.2 (PWT 6.2) constructed by Heston, Summers, and Aten (2006). PWT 6.2 includes 188 countries from the years 1950 – 2004[3]. The data of schooling is from Barro and Lee (2001) that includes the average years of schooling for 107 countries over the period 1960 – 2000.

The rules to choose samples directly follow Mankiw, Romer, and Weil (1992). The selected countries can be further divided into three subsample: the OECD, Non-oil, and Intermediate. The OECD sample consists of the 21 OECD countries. Although this sample has high quality in data, this sample is still small in size. The Non-oil sample with 98 countries excludes OPEC countries because the large part of recorded GDP in OPEC countries is extraction of oil. The Intermediate sample excludes countries whose data receive a grade of "D" from PWT 6.2 or whose populations in 1971 were less than one million. This sample consists of 81 countries. See the Table A.1 in Appendix A for the chosen countries in each of groups.

In addition to the countries growth data used by Mankiw, Romer, and Weil (1992), we add Barro and Lee (2001) human capital data to investigate the relationships between human capital and economic growth. Barro and Lee provide a data set on education attainment for the population over age 25 at five-year intervals between 1960 and 2000. To make these two data sets consistent, the numbers of chosen countries are 21, 76, and 68 in OECD, No-noil, and Intermediate samples when human capital data is considered as a explanatory [4]. Because the human capital data is five-year span from Barro and Lee, we try linear and exponential difference methods to get annual data. Although there are two difference methods to obtain annual human capital data, we find that the estimation results in our convergence model are similar for two types of difference method. We only report Barro and Lee's human capital data by linear difference method in this paper.

Before growth convergence is estimated, We first obtain four cross section dependence test results in the Equation (6) with independent variables as $\ln(y_{i,t-1})$, $\ln(s_{it})$, $\ln(n_{it} + g_i + \delta)$. Then we execute same tests after adding the human capital $\ln(s_{it}^h)$. In Table 1, we summarize the results of tests in the upper panel when we only use saving rate and population growth rate in growth model and in the lower panel when we include Barro and Lee's human capital data into saving and population growth rate. All results in Table 1 imply that we significantly reject the null hypotheses of no cross sectional correlation. Moreover, we can see that all test statistics decline after adding human capital data although we still reject the null hypothesis. It can be explained that if cross countries' dependence is transmitted by technological spillover effects, the level of dependency decline after controlling human capital investment from residuals.

[3] The data set of countries is imperfect, please see the appendix.
[4] We delete Botswana, Lesotho and Togo in Barro and Lee (2001) data set.

Table 1: The results of $LM$, $CD$, $LM_{adj}$ tests, and $\bar{\hat{r}}$

| 1. Before adding human capital | | | |
|---|---|---|---|
| | OECD | Non-oil | Intermediate |
| $LM$ | 27.855 | 18.036 | 15.426 |
| $CD$ | 24.592 | 16.047 | 13.599 |
| $LM_{adj}$ | 20.837 | 12.117 | 10.336 |
| $\bar{\hat{r}}$ | 23.204 | 4.115 | 4.223 |
| **2. After adding Barro-Lee's human capital** | | | |
| | OECD | Non-oil | Intermediate |
| $LM$ | 12.478 | 9.501 | 11.865 |
| $CD$ | 16.063 | 7.892 | 10.793 |
| $LM_{adj}$ | 8.904 | 4.924 | 7.003 |
| $\bar{\hat{r}}$ | 17.954 | 2.745 | 4.199 |

The critical value is 1.96 at 5% significant level.

## 4.2 Estimation

In this section, we compare two estimation results that are with and without controlling for the cross-country dependence in the international growth model. Moreover, we consider the multiple regimes in the growth model and apply the threshold model to estimate different convergence coefficients in different regimes. Throughout these comparisons, we also investigate the regression with out and with Barro and Lee's human capital data. Particularly, we will apply four types of estimation methods in the growth model. First, we use DVLS mrethod to estimate Equation (6). We divide all countries into three groups as Mankiw, Romer, and Weil (1992) and then we use DVLS estimation as a benchmark. The results of this part are summarized at Section 4.2.1.

Second, we consider the cross-section dependence in Equation (6) and use CCEP estimation proposed by Pesaran (2006). In the previous section, we have observed that cross-section dependence existed in the cross-country data of interest. Therefore, we consider CCEP estimation to filter out the transitional growth effects and possible effects of cross-section dependence. The results of this estimation are reported in Section 4.2.1 as well.

Third, we focus on the non-oil sample which include 76 countries like Durlauf and Johnson (1995) and Masanjala and Papageorgiou (2004). We apply the threshold model proposed by Hansen (1999, 2000) and use the initial GDP per capita of each country as the threshold variable. Hansen (2000) considers the threshold model to split countries by initial GDP per capita. Following Hansen's original work we use the logarithm of initial GDP per capita per capita $\ln(y_{i.})$ as a transition variable for threshold and then use DVLS method proposed by Hansen (1999) to estimate coefficients. We calculate all the sum of squared residuals (SSR) under different possible threshold values and choose the threshold which can deliver the minimum SSR as the threshold estimate. We also consider the double threshold model and test the threshold effects by the bootstrap procedure. The results of this estimation are shown in Section 4.2.2.

Finally, in Section 4.2.3, we further consider the possible cross-section dependence in the panel threshold model. We use the logarithm of initial GDP per capita as the threshold variable and CCEP to estimate the threshold model again. We also consider the double panel threshold model under cross section dependence. We compare coefficients from section 4.2.2 and 4.2.3 with other empirical results about Solow growth model.

### 4.2.1 Linear dynamic panel model with and without controlling for cross-section dependence

First, we consider the empirical results without controlling for the cross-sectional dependence. As seen in Table 2, the lagged dependence variables are quite close to one, which indicates that the rates of convergence for the countries in each subsample to their overall growth path are extremely slow if we only consider the invariant country-specific effects. Notice that our results are similar to those in Lee, Pesaran, and Smith's (1997) homogeneity case with annual time dummies, which additionally controls the common transition growth. One potential explanation to this phenomenon is that the overall the averaged impacts is small even if the transition growth might be various across countries. Also notice that our result is quite different from Islam (1995), in which the convergence coefficients in OECD sample is 0.586, in Non-oil sample is 0.776, and in Intermediate sample is 0.794, because we use annual data but he adopts five-year span data over 1960 – 1985. Regarding the effects of schooling on the growth, the coefficient of education measure is only significant in the whole none-oil countries but not in the OECD or Intermediate sample, which indicates that improvement in education can partially help the low-developing counties to catch up to the world growth stream.

Next, consider controlling the effects of cross-sectional dependence by using Pesaran's (2006) CCEP estimation. The results are reported in Table 3. The most significant difference between the results in Tables 2 and 3 is that the convergence coefficients decline, which indicates that the convergence rate to the steady state path becomes faster across all countries if we control the transitional growth effect and filter out possible cross-section dependence in the growth model. Moreover, it is instructive to note that the estimated coefficients $\ln(s_{it})$ is significant only in the OECD sample while the estimates of $\ln(s_{it})$ are positive and significant in Table 3. This result implies that the capital accumulation in the countries except the OECD sample may benefit to the transitional growth effect but insignificantly contribute to the growth to steady state path. Additionally, unlike Table 2 where the coefficients of $\ln(n_{it} + g + \lambda)$ is negative in Intermediate sample, this coefficients becomes insignificant and implies that there does not exist significant effect of population growth on economy growth after controlling the transitional growth effects and filtering out cross-section dependence.

### 4.2.2 Dynamic panel threshold model with fixed individual effects only

We further consider that there exists possible multiple equilibria in cross-country growth model and apply the threshold model to estimate the thresholds. We first try single threshold model and reject the null hypothesis of no threshold effect under 90% confidence level. Next, we try double threshold model and all $p$-values of the double threshold model are less than 10% under different data set, which indicates that there exists three regimes in cross-country growth model. The threshold value in second stage is located on the country of high-level income, for example, on 82nd without human capital and on 62nd country with Barro and Lee's human capital data. The differences of convergence coefficients between middle and high equilibrium are insignificant. Because we do not remove the transitional growth effect here, the insignificant difference between middle and high equilibrium may be caused by the transitional growth effect. If there exists persistent transitional growth effect in the countries of middle-level and high-level income, the speeds of convergence in actual economy growth are very slow among these countries. The estimated results from single and double threshold model are reported in Table 4 and 5. Compared Tables 4 and 5 with 2, the convergence coefficients decrease for the lower income countries, especially in the regression with human capital additionally. Note that the threshold value is located on the country of low-level income, which implies that there exists low equilibrium across the countries of low-level income, and they converge to a low steady state by a faster rate than over all countries. Moreover, the coefficients of human capital become larger and significant in low equilibrium. It implies that the increase in human capital is obviously beneficial to the economy growth in the countries of low-level income. We also find that the coefficients of saving rate have negative effect in the low equilibrium, which indicates that the increase of investment in capital is ineffective and insignificant to the income growth in the countries of low-level income. On the other hand, we find that there still exist positive coefficients of population growth in middle and high equilibrium. This implies that the effects of population growth are inefficient to income growth across the countries of low-level income but beneficial across the middle-level and high-level income countries.

### 4.2.3 Dynamic panel threshold model with both fixed individual effects and cross-section dependence

Finally, let us control for both possible multiple equilibria and cross-section dependence in cross-country growth model. We consider single threshold model first and all $p$-values of testing threshold effect are less than 10%. The threshold value is located on 46th country without human capital data, and 62nd country with Barro and Lees human capital data. We also try double threshold model, but all $p$-values are more then 10%, which indicates that there does not exist low equilibrium when we only care the growth to the steady state path excluding transitional growth effect. Therefore, while the results for two threshold estimation are reported in Table 7, we only focus on the results from single threshold model in Table 6 only.

The threshold value in first stage is located on 46th country without human capital data, and 62nd country with Barro and Lee's human capital data. When we compare Tables 6 and 3, it is obvious that the main difference is that there does not exist three regimes and low and middle-level income countries are merged as a group when we control the transitional growth effect and filter out cross-section dependence. This result implies that if we consider the growth to the steady state excluding the transitional growth effect, the countries of initial low-level and middle-level income will converge to the same steady state; on the other hand, the countries with initial high-level actually converge to the different steady state with the other countries.

We further compare the convergence coefficients between different country groups in the case with Barro and Lee's human capital data. This result indicates that there exists a high equilibrium across the countries of high-level income, and they converge to a high steady state more quickly than the other countries. It implies that the differences of the countries with high initial income diminish very quickly when we filter out the transitional

Table 2: The DVLS estimators : Dependent variable is $\ln(y_{it})$,

1. Without human capital data

| Samples | OECD | Non-oil | Intermediate |
|---|---|---|---|
| Number of countries | (21) | (98) | (81) |
| Time length : 1971 – 2003 | | | |
| $\ln(y_{i,t-1})$ | 0.989* | 0.963* | 0.969* |
| | ( 0.005 ) | ( 0.004 ) | ( 0.004 ) |
| $\ln(s_{it})$ | 0.057* | 0.016* | 0.018* |
| | ( 0.006 ) | ( 0.003 ) | ( 0.003 ) |
| $\ln(n_{it}+g+\delta)$ | 0.009 | 0.021* | -0.020* |
| | ( 0.017 ) | ( 0.007 ) | ( 0.010 ) |

2. With Barro-Lee's human capital data

| Samples | OECD | Non-oil | Intermediate |
|---|---|---|---|
| Number of countries | (21) | (76) | (68) |
| Time length : 1971 – 2000 | | | |
| $\ln(y_{i,t-1})$ | 0.988* | 0.964* | 0.964* |
| | ( 0.010 ) | ( 0.005 ) | ( 0.005 ) |
| $\ln(s_{it})$ | 0.059* | 0.027* | 0.022* |
| | ( 0.007 ) | ( 0.003 ) | ( 0.004 ) |
| $\ln(n_{it}+g+\delta)$ | 0.018 | 0.025* | -0.027* |
| | ( 0.020 ) | ( 0.009 ) | ( 0.012 ) |
| $\ln(s^h_{it})$ | 0.015 | 0.009* | 0.002 |
| | ( 0.014 ) | ( 0.004 ) | ( 0.004 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

effects and cross-section dependence. Besides the convergence coefficients, the coefficients of saving become larger in the countries of high-level income. It shows that the increase of saving is beneficial to growth to the steady state path excluding transitional growth effect.

Table 3: The CCEP estimators : Dependent variable is $\ln(y_{it})$

1. Without human capital data

| Samples | OECD | Non-oil | Intermediate |
|---|---|---|---|
| Number of countries | (21) | (98) | (81) |
| Time length : 1971 – 2003 | | | |
| $\ln(y_{i,t-1})$ | 0.701* | 0.769* | 0.765* |
| | ( 0.087 ) | ( 0.034 ) | ( 0.046 ) |
| $\ln(s_{it})$ | 0.127* | 0.013 | 0.021 |
| | ( 0.032 ) | ( 0.012 ) | ( 0.015 ) |
| $\ln(n_{it} + g + \delta)$ | 0.025 | 0.042 | -0.002 |
| | ( 0.080 ) | ( 0.029 ) | ( 0.040 ) |

2. With Barro-Lee's human capital data

| Samples | OECD | Non-oil | Intermediate |
|---|---|---|---|
| Number of countries | (21) | (76) | (68) |
| Time length : 1971 – 2000 | | | |
| $\ln(y_{i,t-1})$ | 0.599* | 0.711* | 0.637* |
| | ( 0.112 ) | ( 0.044 ) | ( 0.057 ) |
| $\ln(s_{it})$ | 0.129* | 0.019 | 0.029 |
| | ( 0.039 ) | ( 0.017 ) | ( 0.025 ) |
| $\ln(n_{it} + g + \delta)$ | 0.090 | 0.031 | 0.003 |
| | ( 0.085 ) | ( 0.024 ) | ( 0.058 ) |
| $\ln(s^h_{it})$ | 0.112 | -0.034 | -0.046 |
| | ( 0.098 ) | ( 0.076 ) | ( 0.069 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

Table 4: Single threshold model, using DVLS estimation : Dependent variable is $\ln(y_{it})$, and threshold variable is $q_i = \ln(y_{i,1971})$

**1. Without human capital data**

$N = 98$, $T = 33$ (1971 – 2003)
$\hat{\gamma} = 7.0369111$ is located on the 17th country
Test the null hypothesis of no threshold effect: p-value = 0.006

| Regressor | $q_i \leq \hat{\gamma}$ | $q_i > \hat{\gamma}$ |
|---|---|---|
| $\ln(y_{i,t-1})$ | 0.902* | 0.969* |
| | ( 0.015 ) | ( 0.004 ) |
| $\ln(s_{it})$ | -0.004 | 0.022* |
| | ( 0.006 ) | ( 0.004 ) |
| $\ln(n_{it} + g + \delta)$ | -0.052* | 0.036* |
| | ( 0.018 ) | ( 0.008 ) |

**2. With Barro-Lee's human capital data**

$N = 76$, $T = 30$ (1971 – 2000)
$\hat{\gamma} = 6.9483543$ is located on the 5th country
Test the null hypothesis of no threshold effect: p-value = 0.080

| Regressor | $q_i \leq \hat{\gamma}$ | $q_i > \hat{\gamma}$ |
|---|---|---|
| $\ln(y_{i,t-1})$ | 0.778* | 0.966* |
| | ( 0.041 ) | ( 0.005 ) |
| $\ln(s_{it})$ | -0.010 | 0.031* |
| | ( 0.010 ) | ( 0.004 ) |
| $\ln(n_{it} + g + \delta)$ | 0.033 | 0.025* |
| | ( 0.025 ) | ( 0.009 ) |
| $\ln(s^h_{it})$ | 0.037* | 0.008 |
| | ( 0.009 ) | ( 0.005 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

Table 5: Double threshold model, using DVLS estimation: Dependent variable is $\ln(y_{it})$, and threshold variable is $q_i = \ln(y_{i,1971})$

1. Without human capital data

$N = 98$, $T = 33$ $(1971 - 2003)$, $\hat{\gamma}_1 = 7.0369111$, $\hat{\gamma}_2 = 9.4130680$
$\hat{\gamma}_1$ and $\hat{\gamma}_2$ are located on the 17th and 82th country
Test the null hypothesis of single threshold effect: p-value = 0.086

| Regressor | $q_i \le \hat{\gamma}_1$ | $\hat{\gamma}_1 < q_i \le \hat{\gamma}_2$ | $q_i > \hat{\gamma}_2$ |
|---|---|---|---|
| $\ln(y_{i,t-1})$ | 0.902* | 0.966* | 0.972* |
| | ( 0.015 ) | ( 0.004 ) | ( 0.008 ) |
| $\ln(s_{it})$ | -0.004 | 0.021* | 0.038* |
| | ( 0.006 ) | ( 0.004 ) | ( 0.013 ) |
| $\ln(n_{it} + g + \delta)$ | -0.052* | 0.027* | 0.160* |
| | ( 0.018 ) | ( 0.009 ) | ( 0.023 ) |

2. With Barro-Lee's human capital data

$N = 76$, $T = 30$ $(1971 - 2000)$, $\hat{\gamma}_1 = 6.9483543$, $\hat{\gamma}_2 = 9.3761963$
$\hat{\gamma}_1$ and $\hat{\gamma}_2$ are located on the 5th and 62th country
Test the null hypothesis of single threshold effect: p-value = 0.094

| Regressor | $q_i \le \hat{\gamma}_1$ | $\hat{\gamma}_1 < q_i \le \hat{\gamma}_2$ | $q_i > \hat{\gamma}_2$ |
|---|---|---|---|
| $\ln(y_{i,t-1})$ | 0.778* | 0.967* | 0.942* |
| | ( 0.041 ) | ( 0.005 ) | ( 0.015 ) |
| $\ln(s_{it})$ | -0.010 | 0.032* | -0.011 |
| | ( 0.010 ) | ( 0.004 ) | ( 0.013 ) |
| $\ln(n_{it} + g + \delta)$ | 0.033 | 0.019* | 0.179* |
| | ( 0.025 ) | ( 0.010 ) | ( 0.035 ) |
| $\ln(s^h_{it})$ | 0.037* | 0.008 | 0.036* |
| | ( 0.009 ) | ( 0.005 ) | ( 0.019 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

Table 6: Single threshold model, using CCEP estimation : Dependent variable is $\ln(y_{it})$, and threshold variable is $q_i = \ln(y_{i,1971})$

1. Without human capital data

$N = 98$, $T = 33$ (1971–2003)
$\hat{\gamma} = 8.0457471$ is located on the 46th country
Test the null hypothesis of no threshold effect: p-value = 0.020

| Regressor | $q_i \leq \hat{\gamma}$ | $q_i > \hat{\gamma}$ |
|---|---|---|
| $\ln(y_{i,t-1})$ | 0.743* | 0.765* |
| | ( 0.048 ) | ( 0.057 ) |
| $\ln(s_{it})$ | -0.017 | 0.044 |
| | ( 0.015 ) | ( 0.035 ) |
| $\ln(n_{it} + g + \delta)$ | -0.026 | 0.081 |
| | ( 0.041 ) | ( 0.055 ) |

2. With Barro-Lee's human capital data

$N = 76$, $T = 30$ (1971–2000)
$\hat{\gamma} = 9.3761963$ is located on the 62th country
Test the null hypothesis of no threshold effect: p-value = 0.022

| Regressor | $q_i \leq \hat{\gamma}$ | $q_i > \hat{\gamma}$ |
|---|---|---|
| $\ln(y_{i,t-1})$ | 0.734* | 0.499* |
| | ( 0.049 ) | ( 0.043 ) |
| $\ln(s_{it})$ | 0.019 | 0.154* |
| | ( 0.016 ) | ( 0.049 ) |
| $\ln(n_{it} + g + \delta)$ | 0.019 | 0.087 |
| | ( 0.023 ) | ( 0.063 ) |
| $\ln(s^h_{it})$ | -0.034 | 0.139 |
| | ( 0.099 ) | ( 0.114 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

Table 7: Double threshold model, using CCEP estimation: Dependent variable is $\ln(y_{it})$, and threshold variable is $q_i = \ln(y_{i,1971})$

| 1. Without human capital data | | | |
|---|---|---|---|
| $N = 98$, $T = 33$ (1971–2003), $\hat{\gamma}_1 = 6.8013226$, $\hat{\gamma}_2 = 8.0457471$ | | | |
| $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are located on the 8th and 46th country | | | |
| Test the null hypothesis of single threshold effect: p-value = 0.552 | | | |
| Regressor | $q_i \leq \hat{\gamma}_1$ | $\hat{\gamma}_1 < q_i \leq \hat{\gamma}_2$ | $q_i > \hat{\gamma}_2$ |
| $\ln(y_{i,t-1})$ | 0.562* | 0.761* | 0.765* |
| | ( 0.082 ) | ( 0.043 ) | ( 0.053 ) |
| $\ln(s_{it})$ | -0.104* | -0.003 | 0.044 |
| | ( 0.033 ) | ( 0.0124 ) | ( 0.033 ) |
| $\ln(n_{it} + g + \delta)$ | 0.031 | 0.006 | 0.081 |
| | ( 0.116 ) | ( 0.060 ) | ( 0.052 ) |
| 2. With Barro-Lee's human capital data | | | |
| $N = 76$, $T = 30$ (1971–2000), $\hat{\gamma}_1 = 8.0115998$, $\hat{\gamma}_2 = 9.3761963$ | | | |
| $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are located on the 32th and 62th country | | | |
| Test the null hypothesis of single threshold effect: p-value = 0.381 | | | |
| Regressor | $q_i \leq \hat{\gamma}_1$ | $\hat{\gamma}_1 < q_i \leq \hat{\gamma}_2$ | $q_i > \hat{\gamma}_2$ |
| $\ln(y_{i,t-1})$ | 0.771* | 0.704* | 0.499* |
| | ( 0.124 ) | ( 0.044 ) | ( 0.043 ) |
| $\ln(s_{it})$ | 0.002 | 0.033 | 0.154* |
| | ( 0.034 ) | ( 0.021 ) | ( 0.049 ) |
| $\ln(n_{it} + g + \delta)$ | -0.033 | 0.031 | 0.087 |
| | ( 0.082 ) | ( 0.038 ) | ( 0.063 ) |
| $\ln(s^h_{it})$ | -0.040 | 0.023 | 0.139 |
| | ( 0.108 ) | ( 0.094 ) | ( 0.114 ) |

Figures in the parentheses are standard errors.
"$*$" denotes significance at 5%.

# 5 Conclusion

In this research, we examine whether cross section dependence and nonlinearity coexist in growth convergence models with human capital. Our investigations involves three steps. First, we test the cross-section dependence across countries. As the results, there exists cross-section dependence in growth panel no matter human capital is added or not. Second, we use CCEP estimation method to filter out the heterogeneity of technology growth and cross section dependence in the dynamic panel growth model. The convergence coefficients estimated by CCEP are smaller than the coefficients estimated by DVLS. It implies that the speeds of convergence across countries are faster than the speeds in actual economy growth when we control the transitional growth effect and filter out the cross-section dependence.When we further control the human capital, the convergence coefficients and the tests of cross-section dependence decrease. It implies that the human capital may cause the transitional growth effect or the cross-section dependence across countries indirectly. Finally, Finally, we apply the threshold model proposed by Hansen (1999, 2000) to estimate the multiple equilibria in panel data. We find that there does not exist low equilibrium by CCEP estimation. This result implies that the initial low-income and middle-income countries converge to same steady state when we filter out the transitional growth effect and cross-section dependence. We can conclude that we obtain a faster rate of convergence after controlling the transitional growth effect and filtering the cross-section dependence in cross-country data. We also see that there does not exist low equilibrium in growth to steady state unlike in actual economic growth. Because the human capital has the strong correlations with the transitional growth effect and cross-country dependence, we should consider human capital in the dynamic panel data model and treat it more carefully.

For future research, we can extend this analysis to at least two directions. First, the Constant-Elasticity-of-Substitution (CES) production function can be use to analyze the growth convergence and parameter heterogeneity like Masanjala and Papageorgiou (2004). Second, we may consider different threshold variables or transition functions for growth convergence models.

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# Appendix

## Table A.1: Table of countries in each of the samples

( 1 indicates that is chosen in the sample )

| Number | Country | OECD | Non-Oil | Non-Oil (B-L) | Inter-mediate | Inter-mediate (B-L) |
|---|---|---|---|---|---|---|
| 1 | Afghanistan | - | - | - | - | - |
| 2 | Albania | - | - | - | - | - |
| 3 | Algeria | - | - | - | - | - |
| 4 | Angola | - | - | - | - | - |
| 5 | Antigua | - | - | - | - | - |
| 6 | Argentina | - | 1 | 1 | 1 | 1 |
| 7 | Armenia | - | - | - | - | - |
| 8 | Australia | - | 1 | 1 | 1 | 1 |
| 9 | Austria | - | 1 | 1 | 1 | 1 |
| 10 | Azerbaijan | - | - | - | - | - |
| 11 | Bahamas | - | - | - | - | - |
| 12 | Bahrain | - | 1 | 1 | 1 | 1 |
| 13 | Bangladesh | - | - | - | - | - |
| 14 | Barbados | - | 1 | 1 | - | - |
| 15 | Belarus | - | - | - | - | - |
| 16 | Belgium | 1 | 1 | 1 | 1 | 1 |
| 17 | Belize | - | - | - | - | - |
| 18 | Benin | - | 1 | 1 | 1 | 1 |
| 19 | Bermuda | - | - | - | - | - |
| 20 | Bhutan | - | - | - | - | - |
| 21 | Bolivia | - | 1 | 1 | 1 | 1 |
| 22 | Bosnia and Herzegovina | - | - | - | - | - |
| 23 | Botswana | - | 1 | 1 | 1 | 1 |
| 24 | Brazil | - | 1 | 1 | 1 | 1 |
| 25 | Brunei | - | - | - | - | - |
| 26 | Bulgaria | - | - | - | - | - |
| 27 | Burkina Faso | - | 1 | - | 1 | - |
| 28 | Burundi | - | - | - | - | - |
| 29 | Cambodia | - | - | - | - | - |
| 30 | Cameroon | - | 1 | 1 | 1 | 1 |
| 31 | Canada | 1 | 1 | 1 | 1 | 1 |
| 32 | Cape Verde | - | - | - | - | - |
| 33 | Central African Republic | - | 1 | - | - | - |
| 34 | Chad | - | 1 | - | - | - |
| 35 | Chile | - | 1 | 1 | 1 | 1 |
| 36 | China | - | - | - | 1 | - |
| 37 | Colombia | - | 1 | 1 | 1 | - |
| 38 | Comoros | - | - | - | - | - |
| 39 | Congo, Dem. Rep. | - | - | - | - | - |
| 40 | Congo, Republic of | - | 1 | - | 1 | - |
| 41 | Costa Rica | - | 1 | 1 | 1 | 1 |
| 42 | Cote d'Ivoire | - | - | - | - | - |
| 43 | Croatia | - | - | - | - | - |
| 44 | Cuba | - | - | - | - | - |
| 45 | Cyprus | - | 1 | 1 | - | - |
| 46 | Czech Republic | - | - | - | - | - |
| 47 | Denmark | 1 | 1 | 1 | 1 | 1 |
| 48 | Djibouti | - | - | - | - | - |
| 49 | Dominica | - | - | - | - | - |
| 50 | Dominican Republic | - | 1 | 1 | 1 | 1 |
| 51 | Ecuador | - | 1 | 1 | 1 | - |
| 52 | Egypt | - | 1 | - | 1 | - |
| 53 | El Salvador | - | 1 | 1 | 1 | 1 |
| 54 | Equatorial Guinea | - | - | - | - | - |
| 55 | Eritrea | - | - | - | - | - |
| 56 | Estonia | - | - | - | - | - |
| 57 | Ethiopia | - | 1 | - | 1 | - |
| 58 | Fiji | - | 1 | 1 | - | - |
| 59 | Finland | 1 | 1 | 1 | 1 | 1 |
| 60 | France | 1 | 1 | 1 | 1 | 1 |
| 61 | Gabon | - | 1 | - | - | - |
| 62 | Gambia, The | - | 1 | - | - | - |
| 63 | Georgia | - | - | - | - | - |
| 64 | Germany | - | - | - | - | - |
| 65 | Ghana | - | 1 | 1 | 1 | 1 |
| 66 | Greece | 1 | 1 | 1 | 1 | 1 |
| 67 | Grenada | - | - | - | - | - |
| 68 | Guatemala | - | 1 | 1 | 1 | 1 |
| 69 | Guinea | - | 1 | - | 1 | - |
| 70 | Guinea-Bissau | - | - | - | - | - |
| 71 | Guyana | - | - | - | - | - |
| 72 | Haiti | - | - | - | - | - |
| 73 | Honduras | - | 1 | 1 | 1 | 1 |
| 74 | Hong Kong | - | 1 | 1 | 1 | 1 |
| 75 | Hungary | - | - | - | - | - |
| 76 | Iceland | - | 1 | 1 | - | - |
| 77 | India | - | 1 | 1 | 1 | 1 |
| 78 | Indonesia | - | - | - | 1 | 1 |
| 79 | Iran | - | - | - | 1 | 1 |
| 80 | Iraq | - | - | - | - | - |
| 81 | Ireland | 1 | 1 | 1 | 1 | 1 |
| 82 | Israel | - | 1 | 1 | 1 | 1 |
| 83 | Italy | 1 | 1 | 1 | 1 | 1 |
| 84 | Jamaica | - | 1 | 1 | 1 | 1 |
| 85 | Japan | - | 1 | 1 | 1 | 1 |
| 86 | Jordan | - | 1 | 1 | 1 | 1 |
| 87 | Kazakhstan | - | - | - | - | - |
| 88 | Kenya | - | 1 | 1 | 1 | 1 |
| 89 | Kiribati | - | - | - | - | - |
| 90 | Korea, Dem. Rep. | - | - | - | - | - |
| 91 | Korea, Republic of | - | 1 | 1 | 1 | 1 |
| 92 | Kuwait | - | - | - | - | - |
| 93 | Kyrgyzstan | - | - | - | - | - |
| 94 | Laos | - | - | - | - | - |
| 95 | Latvia | - | - | - | - | - |
| 96 | Lebanon | - | - | - | - | - |
| 97 | Lesotho | - | 1 | 1 | - | - |
| 98 | Liberia | - | - | - | - | - |
| 99 | Libya | - | - | - | - | - |
| 100 | Lithuania | - | - | - | - | - |
| 101 | Luxembourg | 1 | 1 | - | - | - |
| 102 | Macao | - | - | - | - | - |
| 103 | Macedonia | - | - | - | - | - |
| 104 | Madagascar | - | 1 | - | 1 | - |
| 105 | Malawi | - | 1 | 1 | 1 | 1 |
| 106 | Malaysia | - | 1 | 1 | 1 | 1 |
| 107 | Maldives | - | - | - | - | - |
| 108 | Mali | - | 1 | 1 | 1 | 1 |
| 109 | Malta | - | 1 | 1 | - | - |
| 110 | Mauritania | - | 1 | - | 1 | - |
| 111 | Mauritius | - | 1 | 1 | - | - |
| 112 | Mexico | - | 1 | 1 | 1 | 1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 113 | Micronesia, Fed. Sts. | - | - | - | - | - |
| 114 | Moldova | - | - | - | - | - |
| 115 | Mongolia | - | - | - | - | - |
| 116 | Morocco | - | 1 | - | 1 | - |
| 117 | Mozambique | - | 1 | - | - | - |
| 118 | Namibia | - | - | - | - | - |
| 119 | Nepal | - | 1 | 1 | 1 | 1 |
| 120 | Netherlands | 1 | 1 | 1 | 1 | 1 |
| 121 | Netherlands Antilles | - | - | - | - | - |
| 122 | New Zealand | 1 | 1 | 1 | 1 | 1 |
| 123 | Nicaragua | - | 1 | 1 | 1 | 1 |
| 124 | Niger | - | 1 | 1 | - | - |
| 125 | Nigeria | - | - | - | 1 | - |
| 126 | Norway | 1 | 1 | 1 | 1 | 1 |
| 127 | Oman | - | 1 | - | - | - |
| 128 | Pakistan | - | 1 | 1 | 1 | 1 |
| 129 | Palau | - | - | - | - | - |
| 130 | Panama | - | 1 | 1 | 1 | 1 |
| 131 | Papua New Guinea | - | 1 | - | - | - |
| 132 | Paraguay | - | 1 | 1 | 1 | 1 |
| 133 | Peru | - | 1 | 1 | 1 | 1 |
| 134 | Philippines | - | 1 | 1 | 1 | 1 |
| 135 | Poland | - | - | - | - | - |
| 136 | Portugal | 1 | 1 | 1 | 1 | 1 |
| 137 | Puerto Rico | - | - | - | - | - |
| 138 | Qatar | - | - | - | - | - |
| 139 | Romania | - | - | - | - | - |
| 140 | Russia | - | - | - | - | - |
| 141 | Rwanda | - | - | - | - | - |
| 142 | Samoa | - | - | - | - | - |
| 143 | Sao Tome and Principe | - | - | - | - | - |
| 144 | Saudi Arabia | - | - | - | - | - |
| 145 | Senegal | - | 1 | 1 | 1 | 1 |
| 146 | Serbia and Montenegro | - | - | - | - | - |
| 147 | Seychelles | - | - | - | - | - |
| 148 | Sierra Leone | - | 1 | 1 | 1 | 1 |
| 149 | Singapore | - | 1 | 1 | 1 | 1 |
| 150 | Slovak Republic | - | - | - | - | - |
| 151 | Slovenia | - | - | - | - | - |
| 152 | Solomon Islands | - | - | - | - | - |
| 153 | Somalia | - | - | - | - | - |
| 154 | South Africa | - | 1 | 1 | 1 | 1 |
| 155 | Spain | 1 | 1 | 1 | 1 | 1 |
| 156 | Sri Lanka | - | 1 | 1 | 1 | 1 |
| 157 | St. Kitts and Nevis | - | - | - | - | - |
| 158 | St. Lucia | - | - | - | - | - |
| 159 | St.Vincent and Grenadines | - | - | - | - | - |
| 160 | Sudan | - | 1 | 1 | - | - |
| 161 | Suriname | - | 1 | - | - | - |
| 162 | Swaziland | - | 1 | 1 | 1 | 1 |
| 163 | Sweden | 1 | 1 | 1 | 1 | 1 |
| 164 | Switzerland | 1 | 1 | 1 | 1 | 1 |
| 165 | Syria | - | 1 | - | 1 | 1 |
| 166 | Taiwan | - | 1 | 1 | - | - |
| 167 | Tajikistan | - | - | - | - | - |
| 168 | Tanzania | - | 1 | - | 1 | - |
| 169 | Thailand | - | 1 | 1 | 1 | 1 |
| 170 | Togo | - | 1 | 1 | - | - |
| 171 | Tonga | - | - | - | - | - |
| 172 | Trinidad and Tobago | - | 1 | 1 | - | - |
| 173 | Tunisia | - | 1 | 1 | 1 | 1 |
| 174 | Turkey | 1 | 1 | 1 | 1 | 1 |
| 175 | Turkmenistan | - | - | - | - | - |
| 176 | Uganda | - | 1 | 1 | - | - |
| 177 | Ukraine | - | - | - | - | - |
| 178 | United Arab Emirates | - | - | - | - | - |
| 179 | United Kingdom | 1 | 1 | 1 | 1 | 1 |
| 180 | United States | 1 | 1 | 1 | 1 | 1 |
| 181 | Uruguay | - | 1 | 1 | 1 | 1 |
| 182 | Uzbekistan | - | - | - | - | - |
| 183 | Vanuatu | - | - | - | - | - |
| 184 | Venezuela | - | - | - | 1 | 1 |
| 185 | Vietnam | - | - | - | - | - |
| 186 | Yemen | - | - | - | - | - |
| 187 | Zambia | - | 1 | 1 | 1 | 1 |
| 188 | Zimbabwe | - | 1 | 1 | 1 | 1 |
| total | | 21 | 98 | 79 | 81 | 68 |