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International spillovers in a world of technology clubs

Roman Stöllinger[1]

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JEL: O47, O41, I25, O33
Keywords: technology clubs, threshold regressions, technology spillovers, Schumpeterian growth model, human capital

Author

[1] Wiener Institut für Internationale Wirtschaftsvergleiche, Rahlgasse 3, 1060 Wien, Austria; Email: stoellinger@wiiw.ac.at

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[◊] Wiener Institut für Internationale Wirtschaftsvergleiche, Rahlgasse 3, 1060 Wien, Austria
stoellinger@wiiw.ac.at

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1 Introduction

Technology is a key component of long-term growth and successful economic development. In an international context this implies that countries' economic growth does not only depend on domestic technological progress but also on technological developments abroad. If one assumes that technological progress – be it by way of *(i)* innovation or *(ii)* by imitation of existing foreign technologies – is a costly process, not all countries will grow at the same rate. Therefore the level of technology (and hence productivity) differs greatly across countries, a fact which is hardly disputed.

One of the objectives in this paper is to use technology and human capital related indicators to classify countries according to their technological capacity. A country's technological capacity, in a broad sense, depends on both its capability to undertake research and development (R&D) and innovate and its ability to absorb foreign technologies that have been developed abroad. R&D and imitation represent two distinct activities that both feed into technological progress. While innovations add to the existing (global) technology stock and shifts the (global) technological frontier outward, imitation is the process of being able to make productive use of existing innovations. The ability to imitate and adopt foreign technologies for local use must be assumed to be a highly human capital and knowledge intensive process (as are original innovation and R&D). For this reason we follow Nelson and Phelps (1966) in assuming that the capacity to benefit from foreign technologies via international spillovers depends primarily on the level of human capital available in the country. Hence, while it is true that countries with low levels of productivity have a high potential for receiving technology spillovers, de facto, they may find it hard to benefit from such spillovers because of the lack of human resources required for the imitation process. In this case Gershenkron's famous "advantage to backwardness" is counteracted by a lack of absorptive capacity.

Countries will perform neither innovation nor imitation activities if their levels of human capital do not meet the required threshold to undertake R&D and/or imitate foreign technologies. For example, R&D and patenting are highly concentrated activities with the EU, the US and Japan alone accounting for more than two thirds of the global expenditure on R&D in 2007 while the Sub-Saharan countries undertake very little R&D, a mere 0.5% of global R&D expenditures (UNESCO, 2010).

Countries undertaking either innovation, imitation or none may diverge on different growth paths and/or end up at different income levels. This constellation gives rise to the notion of convergence clubs suggesting a tripartite world consisting of an "innovation group", an "imitation group" and a "stagnation group". The innovation group includes countries that perform R&D and innovate thereby pushing the global technological frontier outward. Countries in the imitation group do not undertake R&D themselves but take on new technologies developed abroad through the absorption of foreign technologies. The stagnation group has insufficient endowments of human capital and skills in order to adopt and implement new foreign technologies. Therefore the countries in this group have very high technology gaps, that is, the difference in their productivity level to the country with the highest productivity.

As pointed out above we will use technology (R&D expenditure) and human capital related variables (literacy rate, years of schooling) to cluster countries into technology clubs. As it turns out, we find three rather distinct clubs which fit well the idea of innovation, imitation and stagnation groups.

In the second part of the paper, we test whether we can detect catch-up effects - that is growth effects from an existing technology gap – in a growth regression framework and to what extent these catch-up effects are associated with a country's absorptive capacity. Our simple growth equation contains, next to the traditional factors of production, a capacity technology gap variable which is intended to capture the growth effects associated with international technology spillovers.

We employ the threshold regression approach developed by Hansen (1996, 1999, 2000) to allow for non-linearities in the catch-up effects of countries, splitting the sample along the human capital dimension. We find that for countries with intermediate levels of human capital there is a large catch-up effect, i.e. countries can to some extent translate their technology gap into higher growth. At the same time such a catch-up process cannot be taken for granted as countries with very low levels of human capital enjoy only limited growth effects from their technology gaps – though their technology gaps tends to be large.

The paper proceeds as follows: Section 2 discusses some of the related literature. Section 3 gives the data sources used in sections 4 and 5 which contain the results of our cluster analysis and the growth regressions respectively. Section 6 concludes.

2 Related literature

The conceptual background for this paper is the endogenous growth literature. Endogenous growth literature explicitly models the law of motion for technology and productivity instead of assuming it to be an exogenous process.

In the model by Aghion and Howitt (1992) firms push the technological frontier by investing in R&D. Firms which come up with a successful innovation gain a temporary monopoly for the production of goods that lasts until it is replaced by the next innovator. Other firms (which are also potential innovators) can build on the innovative contributions of previous innovators so that each new innovation pushes out the technological frontier. Howitt (2000) provides a multicountry version of the Aghion-Howitt growth model. In this model, R&D performing countries with lower productivity will grow at the same pace as the leading country though it will not catch-up in terms of per capita income. The mechanism that ensures growth convergence is that if a firm innovates successfully, it brings the sectors productivity up to the *global* technological frontier. However, not all countries necessarily perform R&D so that some countries will not innovate at all and therefore stagnate giving rise to club convergence (in growth rates).

In an extension of the Howitt (2000) growth model Howitt and Mayer-Foulkes (2005) develop a model with two types of technological advances: *(i)* R&D activity leading to innovations and *(ii)* imitation which is the process of implementing existing foreign technologies. Both innovation and imitation are skill intensive activities. In the convergence club model of Howitt and Foulkes (2005) – which is our main theoretical reference model – countries select themselves into three groups, depending on their technological capabilities. A group of technologically advanced countries will perform R&D and come up with new innovations. This innovation club pushes the global technological frontier. A second group of countries, the imitation club, is successful in imitating and adapting existing technologies previously developed by the innovation group. In contrast, their level of productivity and human capital does not allow them to undertake original R&D. The imitation group successfully implements existing technologies because they have the required level of absorptive capacity which in turn depends on human capital. Here the idea developed by Nelson and Phelps (1966) that countries can benefit from their technology gap vis-à-vis leading countries because it enables them to strongly draw on the existing technology (or knowledge) stock. As in several related models, the imitators and the R&D leaders converge to the same growth path but the former will not succeed in catching-up in terms of per-capita income (e.g. Acemoglu and Ventura, 2002; Howitt 2000).

Finally, there is a third group, the stagnation club, which consists of initially backward countries whose low levels of absorptive capacity prevent them from catching-up with the continuously expanding global technological frontier. These backward countries are trapped in a zero growth equilibrium and will fall behind in terms of productivity and GDP per capita leading to an ever increasing technology gap.

The idea of convergence clubs is also related to the concept of poverty traps (see e.g. Azariadis and Drazen, 1990; Azariadis, 1996) through the high importance attributed to initial conditions and threshold effects. In the poverty trap literature diverging growth regimes are the result of threshold externalities in accumulative factors (Azariadis and Drazen, 1990). A country may be trapped in a low growth, low income equilibrium for several reasons including demography, impatience, institutions (corruption), globalisation or technology (see Azariadis, 1996). The convergence clubs literature also relies on threshold effects that lead to a bifurcation in the law of motion of the countries' growth rates but it assigns the threshold effects to the technological realm, i.e. the innovative and the absorptive capacity of countries.

Empirically the notion of convergence clubs received support from findings on the existence of multiple growth regimes (Durlauf and Johnson, 1995) and research on the world income distribution which in the modern era saw the emergence of "twin peaks" (e.g. Quah, 1997). The existence of a bimodal distribution of per-capita income across countries implies an accumulation of countries at very different levels of income. Convergence of countries to different per capita incomes is clearly incompatible with a general growth convergence among all countries but perfectly in line with convergence within clubs.

Closely related to our work are the contributions by Castellacci (2008; 2010) and Castellacci and Archibugi (2008) who take up the issue of technology clubs empirically and use cluster techniques in order to sort countries into three technology clubs. Castellacci (2008) uses the number of journal articles as a proxy for innovative capacity and the literacy rate of the population representing absorptive capacity. We undertake a similar exercise, though our variables for the cluster analysis are different since we use the gross expenditure on R&D as a percentage of GDP as a technology variable and the literacy rate and the average years of schooling as a proxy for absorptive capacity. Moreover, our cluster analysis is different from Castellaci (2008) who employs a classification and regression tree (CART) analysis on top of a hierarchical cluster analysis. The CART analysis subsequently determines the thresholds to distinguish clearly between the innovative, the imitation and the stagnation club, starting with the split between the stagnation and the imitation group.

Our approach simply combines a hierarchical cluster analysis with a non-hierarchical cluster approach. The advantage of our approach, however, is that the number of clusters is not predetermined but is based on a decision rule. Nevertheless we also end up with a tripartite cluster solution.

For our growth regressions we draw heavily on Benhabib and Spiegel (1994) and Crespo, Martín and Velázques (2004) as the growth equation we estimate is similar to their specifications. Starting from a Cobb-Douglas production function Benhabib and Spiegel (1994) endogenise the productivity term by introducing a law of motion for productivity. According to this law of motion for productivity, the change in productivity is a function of human capital and the country's distance to the technological frontier, i.e. the technology gap. Econometrically, the Benhabib-Spiegel approach leads to the substitution of the growth rate of human capital with the *level* of human capital. Benhabib and Spiegel also introduce a catch-up term which is created by interacting human capital with the technology gap. We will employ this catch-up term for measuring the growth effects from spillovers. In addition we will estimate our growth regression with the simple technology gap variable. The growth regression we estimate resembles that of Crespo, Martín and Velázques (2004) who estimate the growth effects of spillovers for a sample of OECD countries using the interaction between human capital and the technology gap as the catch-up variable.

We add to the existing literature on spillovers and absorptive capacity by searching for non-linearities in the spillover effect by splitting the sample into sub-samples where countries are sorted into these sub-samples according to their level of human capital. To this end we employ the threshold estimation technique developed by Hansen (2000). The main advantage of the threshold estimation procedure is that the threshold that splits the sample is not determined a priori but is determined by the data during the estimation process. Hence, the threshold regression technique is an alternative method to account for the potential human capital related non-linearity in the effect of the technology gap on economic growth.

We detect thresholds in the human capital variable and relate them to the technology club literature. Given this theoretical framework we expect to find (at least) three different regimes with respect to the catch-up effect which we associate with the innovation, the imitation and the stagnation club. Moreover, we expect that the medium regime resulting from the threshold regressions – which we associate with the imitation club – to benefit most strongly form spillovers and that they therefore have the largest growth effects from the catch-up variable. In contrast, no or at least a smaller growth effect from spillovers are expected for the low regime, i.e. the country group with the lowest level of human capital which we associate with the stagnation club.

3 Data

Our primary source of data is the World Bank's World Development Indicators (WDI) database. From the WDI we take GDP per capita, gross fixed capital formation, labour force and population data as well as the literacy rate of the population aged 15 or over. We collect these variables for the period 1980-2009. We complement the human capital variables with data from the Barro-Lee database from which we use the average years of schooling. Our main innovation variable is gross expenditure on R&D (GERD) as a percentage of GDP for which – due to our global coverage of countries – we turn to the UNESCO Institute for Statistics (UIS) data on Science and Technology indicators. The principal time coverage of the UNESCO data base is from 1996 to 2007.

For the cluster analysis we have to impute some of the data in order to end up with a satisfactorily large dataset. In particular we lack data on the literacy rate for most developed countries as this type of data is typically not collected anymore. Hence, we follow the approach of UNEP in their calculation of the Human Development Index (HDI) and assume a literacy rate of 99% for these countries. Moreover, UNEP provides literacy rate data for some countries where the

WDI databank does not, so we complement the WDI data with UNEP data in these instances. Unfortunately, we also lack data on the R&D expenditure for a rather large number of countries, and in particular for African countries. In order not to lose too many observations we rely on regional averages provided by UNESCO (2010), except for the LDC countries where we apply the LDC's average rate. While this may be seen as a shortcoming of our approach for the clustering analysis we believe that the regional approximations are a permissible imputation method as we do not expect any serious outliers in the group of missing countries. In some instances, where we feel uneasy about using the region's average we either use the value of a neighbouring country or drop the country from the sample.

The capital stocks needed for the growth regressions are calculated with the perpetual inventory method with 1980 as the base year. We assume a depreciation rate of 6% (as Hall, 1999) and use the 1980-2005 annual growth rate to arrive at the capital stock in 1980.

4 Identifying technology clubs

Given our hypothesis of distinct technology clubs based on innovative and absorptive capacities, we first try to identify such convergence clubs and its members by way of cluster analysis. There exists a wide range of potential variables that may reflect the technological capacity and absorptive capacity of countries. As in Castellacci (2008) we adapt a parsimonious approach with respect to the number of variables we use for the cluster analysis. We rely on gross expenditure on R&D as a share of GDP to proxy for the innovative capability of countries. With respect to absorptive capacity we take the Nelson and Phelps (1966) view that the level of human capital is the main determinant of absorptive capacity. We use two human capital indicators, namely the literacy rate and the average years of schooling. The choice of these variables is to a large extent also determined by the availability of data. We base the analysis on the data for the average of the years 2005-2009.

The cluster analysis is performed in two steps. We start out with a hierarchical cluster analysis using the average linkage method. This delivers a first clustering result for a total of 142 countries with the number of groups (or clubs) not being pre-determined. We use the Calinski-Harabasz method as a stopping rule for determining the number of clubs. In a second step we use a non-hierarchical cluster analyses that starts out with a given number of clubs which we obtained from the hierarchical cluster analysis. The advantage of the non-hierarchical cluster process is that it allows repeated resorting of countries into different clusters during the course of the clustering process which is not the case in a hierarchical cluster process. The possibility of resorting countries tends to lead to more distinct clusters each with more similar elements. However, in the non-hierarchical cluster procedure the number of clusters is determined ex-ante.

The hierarchical clustering procedure delivers a first cluster result with the stopping rule and the cluster tree suggesting either a clustering into 3 or 6 distinct country groups[1,2]. As a next step we perform a non-hierarchical cluster analysis imposing alternatively 3, 4, 5 or 6 clusters. In our case the results from both methods are rather similar with only a slight reordering of countries. Comparing the values of Calinski-Harabasz stopping rule for the non-hierarchical cluster solutions with alternative numbers of pre-defined clusters confirms the preferred number of clubs being three. The result from our cluster analysis is presented in Tables 1a and 1b.

The first cluster consists of 38 countries with low values of both the innovation and the human capital variables. The group average for the R&D expenditure in percentage of GDP (R&D/GDP) is only 0.26%. The average literacy rate is just above 60% with the average person having about 4.3 years of schooling. Given our theoretical model we label this cluster the stagnation club (or marginalised group). Note also that this club comprises about a third of the total population of all the countries in the sample. The second cluster, which is the largest comprising 80 members, also scores low on the R&D dimension with a R&D/GDP ratio of about 0.5%. However, the human capital levels are rather high with a literacy rate of about 93% and on average almost 8.5 years of schooling. The characteristics of this cluster fits well with the notion of the imitation club whose members do not perform a lot of their own R&D but are quite capable of adopting foreign technologies. Finally, the third cluster includes 24 countries with a high R&D/GDP ratio amounting to 2.2%, close to complete literacy among the population and on average 10.7 years of schooling. These characteristics we associate with the innovation club consisting of the technology leaders.[3]

[1] We exclude Israel from the analysis as it represents an outlier due to its very high R&D expenditures.
[2] In Calinski-Harabasz method large values for the Pseudo-F value suggest more distinct clusters. For the cluster dendrogram and the results for the different cluster solution see Appendix A4.
[3] The result from the cluster analysis remains qualitatively the same if we perform the cluster analysis with a reduced country sample for which R&D data is available with hardly any differences in the club membership of the countries in the two methods. The major difference is that the number of the members in the stagnation club is largely reduced because of the many missing African countries.

Table 1a: Characteristics of the technology Clubs resulting from the cluster analyses, 2005-2009

cluster #		R&D expenditure (% of GDP)	literacy rate (in %)	average years of schooling	number of countries	assigned name of club	share of total population
1	cluster mean	0.26	60.02	4.27	38	stagnation	34.26
	std. dev.	0.16	14.14	1.37		(marginalized)	
	min	*0.03 (Sambia)*	*26.2 (Mali)*	*1.24 (Mozambique)*			
	max	*0.80 (India)*	*84.2 (Syria)*	*7.50 (Ghana)*			
2	cluster mean	0.47	92.94	8.41	80	imitation	52.24
	std. dev.	0.31	6.23	1.52		(follower)	
	min	*0.04 (Saudi Arabia)*	*72.6 (Algeria)*	*4.15 (Myanmar)*			
	max	*1.40 (China)*	*99.8 (Latvia, Cuba)*	*11.49 (Hungary)*			
3	cluster mean	2.22	98.88	10.74	24	innovation	13.50
	std. dev.	0.74	0.92	1.23		(leader)	
	min	*1.12 (Estonia)*	*94.7 (Singapore)*	*8.47 (Singapore)*			
	max	*3.68 (Sweden)*	*99.8 (Estonia)*	*12.75 (Czech Republic)*			

Note: Club averages are unweighted averages based on country values. (e.g. China and Macao are two distinct reporters here). Literacy rate of population aged 15+. The three technology clubs include the following countries:
Stagnation club: Cote d'Ivoire, Papua New Guinea, Haiti, Central African Republic, Congo, Dem. Rep., Mozambique, Burundi, Gambia, Senegal, Mal, Benin, Mauritania, Nepal, Bangladesh, Togo, Liberia, Pakistan, Morocco, Niger, India, Afghanistan, Rwanda, Sudan, Sierra Leone, Yemen, Rep., Guatemala, Malawi, Iraq, Syrian Arab Republic, Lao PDR, Ghana, Congo, Rep., Tanzania, Uganda, Zambia, Cameroon, Egypt, Arab Rep., Cambodia.
Imitation club: Ecuador, Latvia, Tunisia, Tonga, Maldives, Algeria, Mauritius, Belize, Romania, Cuba, Panama, Mexico, Tajikistan, Malaysia, Nicaragua, Iran, Islamic Rep., Trinidad and Tobago, El Salvador, Macao SAR, China, Jordan, Qatar, Italy, Costa Rica, Lesotho, Bolivia, Jamaica, Poland, Serbia, Bahrain, Slovak Republic, Portugal, Gabon, South Africa, Zimbabwe, United Arab Emirates, Libya, Croatia, Paraguay, Bulgaria, Venezuela, RB, Indonesia, Botswana, Kuwait, Vietnam, Namibia, Malta, Saudi Arabia, Mongolia, Swaziland, Turkey, Kazakhstan, Cyprus, Moldova, Russian Federation, China, Dominican Republic, Greece, Myanmar, Chile, Thailand, Sri Lanka, Colombia, Albania, Honduras, Argentina, Kenya, Barbados, Armenia, Brazil, Kyrgyz Republic, Philippines, Fiji, Spain, Peru, Hong Kong SAR, China, Uruguay, Guyana, Hungary, Lithuania, Ukraine.
Innovation club: Austria, Estonia, France, Canada, Singapore, Iceland, Germany, Finland, United Kingdom, United States, Australia, Korea, Rep., Czech Republic, Netherlands, Japan, Sweden, Ireland, Belgium, New Zealand, Denmark, Switzerland, Slovenia, Luxembourg, Norway.

The result of the cluster analysis is to a large extent as expected and contains only few surprises. Most OECD countries are in the innovation club while the stagnation club is formed mostly by African countries supplemented by a few Central Amerian countries, e.g. Haiti, and Asian countries (e.g. Laos, Cambodia). One of the few surprises is that Estonia end up in the innovation club. The second surprise in our clustering result is the fact that India is sorted into the stagnation club, despite a rather high R&D/GDP ratio. For example, India's R&D/GDP ratio is higher than that of China. The reason why in our analysis India ends up in the stagnation club is its still very low literacy rate.[4]

[4] According the UNDP's Human development index India's literacy rate would be somewhat higher, around 66% for the period 1999-2007. In order to be in line with the majority of the other countries we stick to the World Bank data (WDI) for the Indian literacy rate. Moreover, there are vast difference in

Table 1b shows the differences in the clubs' means across the three variables. As can easily be seen, there is a huge difference between the innovation group (cluster 3) and the imitation group (cluster 2) in terms of R&D/GDP amounting to 1.75 percentage points which is more than three times the current value of the imitation group. In contrast, the differences between these two groups in the literacy rate and average years of schooling are less dramatic as the imitation group also scores high on these dimensions. The opposite situation can be observed when comparing the imitation club with the stagnation club as the difference in the R&D/GDP-ratio is small relative to the differences in the human capital variables. Therefore it seems that the distinctive feature separating the innovation club from the imitation club is indeed primarily the R&D/GDP ratio while the imitation club and the stagnation club mainly differ in terms of human capital which we claim is relevant for a country's absorptive capacity. The differences in the clubs' means in all three dimensions are statistically significant according to standard t-tests.

Table 1b: Differences between the Technology Clubs (cluster means), 2005-2009

cluster #	**R&D expenditure (% of GDP)**	**literacy rate (in %)**	**average years of schooling**
3-2	1.75	5.95	2.33
	(16.87)	(4.64)	(6.84)
3-1	1.96	38.86	6.47
	(15.77)	(13.41)	(18.78)
2-1	0.20	32.92	4.14
	(3.76)	(17.59)	(14.24)

Note: Differences in R&D expenditures and literacy rates in percentage points; differences in average years of schooling in years; t-values in parenthesis.

5 Estimating Growth Effects of Technology Spillovers

The tripartite technology cluster solution presented in the previous section is based on the assumption that countries with different characteristics benefit to varying degrees from foreign technology spillovers. In this section we investigate whether we can detect such spillovers in a growth regression framework. We associate these spillovers with the effect of a catch-up term on economic growth where this catch-up term is an interaction of the technology gap and human capital. In particular we are interested whether the strength of such growth effects from the catch-up term vary with the level of human capital.

the literacy rates within India. According to Indian census figures from 2001, literacy rates in India range from only 47% in Bihar to more than 90% in Kerala. See http://india.gov.in/knowindia/literacy.php.

The starting point is the traditional (Cobb-Douglas) production function. By taking logs and first differences we get:

$$(1)\qquad \Delta ln\, Y_{it} = \alpha \cdot \Delta ln\, K_{it} + \beta \cdot \Delta ln\, L_{it} + \Delta lnA_{it} + \varepsilon_{it}$$

where ΔlnY_{it} is the growth rate of GDP of country *i* in period *t*, ΔlnK_{it} is the growth rate of the physical capital stock, ΔlnL_{it} is the growth rate of labour and ΔlnA_{it} is total productivity productivity growth. ε_{it} denotes the error term.

In line with the endogenous growth literature we assume a law of motion for productivity which takes the form

$$(2)\qquad \Delta \ln A_{it} = \gamma + \delta \cdot \mathrm{H}_{it} + \phi(H_{it}) \cdot \left(\frac{A_t^{max} - A_{it}}{A_t^{max}}\right)$$

Equation (2) assumes that the change in productivity depends on the *stock* of human capital, H_{it} which we proxy by the average years of schooling and the technology gap. While there are alternative definitions of the technology gap in the literature, we opt for calculating country *i*'s technology gap as the difference between the technologically leading country's productivity and the productivity of country *i*, divided by the leader's productivity. In our sample the United States is the technology leader throughout the periods. The productivity of country *i* is derived from the Cobb-Douglas production function following Hall and Jones (1999) yielding $\mathrm{A}_i = \frac{\frac{Y_i}{L_i}}{\left(\frac{K_i}{Y_i}\right)^{\frac{\propto}{1-\propto}}}$.

Equation (2) is basically the Benhabib and Spiegel (1994) framework which stresses the (mainly indirect) role of human capital for the growth process through the impact on productivity growth.

Note that in equation (2) the coefficient of the technology gap, ϕ, is a function of human capital, H_{it}. This is because the potential for catching up of countries with a technology gap is expected to depend on the country's absorptive capacity which we proxy by human capital. A country's absorptive capacity, according to Cohen and Levinthal (1989), is "the ability to identify, assimilate, and exploit knowledge from the environment" – in our case from other countries. Many other variables may matter for absorptive capacity but here we want to focus on human capital as enabling factor for technology spillovers.

Using human capital as proxy for a country's absorptive capacity implies that human capital has a double role: it feeds directly into productivity growth but it is also relevant for the potential spillovers that arise from the technology gap.

As mentioned earlier, a common proxy for the absorption of spillovers is the catch-up term used by Benhabib and Spiegel (2005) and Crespo, Martín and

Velázques (2004) which is built by interacting human capital with the technology gap, $\mathrm{H_{it}} \cdot \frac{\mathrm{A_t^{max}}\text{-}\mathrm{A_{it}}}{\mathrm{A_t^{max}}}$. In this case the law of motion for productivity becomes:

$$(2') \qquad \Delta \ln A_{it} = \gamma + \delta \cdot \mathrm{H}_{it} + \phi \cdot \left(H_{it} \cdot \frac{A_t^{max} - A_{it}}{A_t^{max}} \right)$$

Combining equation (2′) with equation (1) yields the following growth regression:

$$(3) \qquad \Delta \ln Y_{it} = \gamma + \alpha \cdot \Delta ln\, K_{i,t} + \beta \cdot \Delta \ln L_{i,t} + \delta \cdot \mathrm{H}_{i,t-1} + \phi \cdot \left(H_{i,t-1} \cdot GAP_{i,t-1} \right) + \eta_t + \mu_i + \varepsilon_{i,t}$$

where $\mathrm{GAP_{i,t\text{-}1}}$ is defined as $\left(\frac{A_{t-1}^{max} - A_{i,t-1}}{A_{t-1}^{max}} \right)$ and $\left(\mathrm{H_{i,t\text{-}1}} \cdot \mathrm{GAP_{i,t\text{-}1}} \right)$ is the catch-up term. In our empirical application we use lagged values of the human capital stock as well as the technology gap and we include time dummies (η_{it}) and country dummies (μ_{it}).

In this specification the main variable of interest is the catch-up term. The coefficient of the catch-up term is intended to capture the growth effect induced by international technology spillovers. Obviously, we expect a larger growth effect for countries with a large technology gap (as they have the highest potential for international technology spillovers) and larger human capital stocks (as they have higher absorptive capacity). In other words we expect a positive sign for the coefficient ϕ.

The main contribution of this paper is the use of threshold regressions to take into account that the strength of the growth effect may depend on the level of human capital. Hence, instead of building an interaction term between the technology gap and human capital we directly use the coefficients of the technology gap variable to measure the catch-up effects. In the threshold regression framework we chose human capital to be the threshold variable. This means that during the estimation process the sample is split into two (or more) sub-samples. The countries are allocated into the respective sub-sample on the basis of their human capital stock. Countries with levels of human capital below a certain threshold are allocated into a first sub-sample (low regime) and countries with human capital stocks above the threshold form the second sub-sample (high regime). The sample splitting allows introducing non-linearities in any dependent variable. For our purposes it is appropriate to allow for non-linear effects of the technology gap on growth. The non-linearity arises from the fact that the coefficients of the technology gap may be different for the sub-samples which result from the sample-split.

In the threshold regression framework our spillover model takes the form:

(4)

$$\Delta ln\, Y_{it} = \gamma + \alpha \cdot \Delta ln\, K_{it} + \beta \cdot \Delta ln\, L_{it} + \delta \cdot \mathrm{H}_{i,t-1} + \theta_1 \cdot (GAP_{i,t-1})(if\ \mathrm{H}_{i,t-1} \leq \lambda) + \\ + \theta_2 \cdot (GAP_{i,t-1})(if\ \mathrm{H}_{i,t-1} > \lambda) + \eta_t + \mu_i + \varepsilon_{it}$$

where λ denotes the threshold in the human capital variable.

5.1 Results from OLS regressions

Before we implement this threshold regression we first test whether we can detect growth effect from the catch-up term and the technology gap respectively by ordinary least square (OLS) regressions. So we run pooled panel and fixed effects estimation of equation (3).

Our sample is a balanced panel of 76 countries for the time span 1980-2009 where we divide this time span into six 5-year periods. Since we estimate (log) differences we end up with a panel of dimensions *i=76* and *t=5*.

The results from the OLS panel regression are presented in Table 3.

Table 3: OLS estimation of growth effects from spillovers

Dependent variable: Δ log GDP per capita *(Δ ln Y_{it})*

	Pooled		Fixed effects		
	base (1)	full (2)	base (3)	full (4)	productivity gap (5)
$\Delta \ln K_{i,t}$	0.4854 ***	0.4802 ***	0.4157 ***	0.4320 ***	0.4323 ***
	0.035	0.035	0.065	0.063	0.063
$\Delta \ln L_{i,t}$	0.2312 **	0.2076 *	0.3846 **	0.3848 **	0.3824 **
	0.097	0.105	0.173	0.171	0.167
$H_{i,t-1}$	-0.0039 *	0.0046	-0.0601	-0.0124	-0.0103
	0.002	0.005	0.014	0.016	0.011
$(HxGAP)_{i,t-1}$	0.0092 ***	0.0001	0.0610 ***	0.0026	
	0.003	0.006	0.011	0.020	
$(GAP)_{i,t-1}$		0.0935		0.8161 ***	0.8446 ***
		0.063		0.255	0.142
constant	0.0607	-0.0221	0.2339	-0.4407 **	-0.4643 ***
	0.021	0.051	0.097	0.198	0.141
time dummies	no	no	yes	yes	yes
country dummies	no	no	yes	yes	yes
F-test	70.207	58.978	12.167	12.311	13.792
R^2	0.421	0.423	0.595	0.606	0.606
R^2-adj.	0.415	0.415	0.482	0.494	0.496
Obs.	380	380	380	380	380

Note: Estimated with STATA 11. Robust standard errors are shown below the coefficients. ***, **, * indicate statistical significance at the 1%, 5% and 10% level respectively.

In columns (1) and (2) we estimate a pooled version of equation (3) but since the results are qualitatively similar we can immediately proceed to the fixed effects results (columns 3-5).

In the base specification we include the (lagged) catch-up term to measure growth effects from a human capital stock adjusted technology gap. Note that we include centred values of $\mathrm{H}_{i,t-1}$ and $GAP_{i,t-1}$ in order to avoid a misspecification related to the fact that the catch-up variable is an interaction term.

The results are largely as expected: we find a positive and statistically highly significant effect for the growth rate of the capital stock. Specification (3) suggests that a 1 percentage point increase in the growth of the capital stock increases the GDP growth by 0.42 percentage points.[5] The coefficient of the growth rate of the labour force is also positive, statistically significant and economically large[6]. The stock of human capital is positive but not statistically significant, a result often find in growth regressions including human capital.

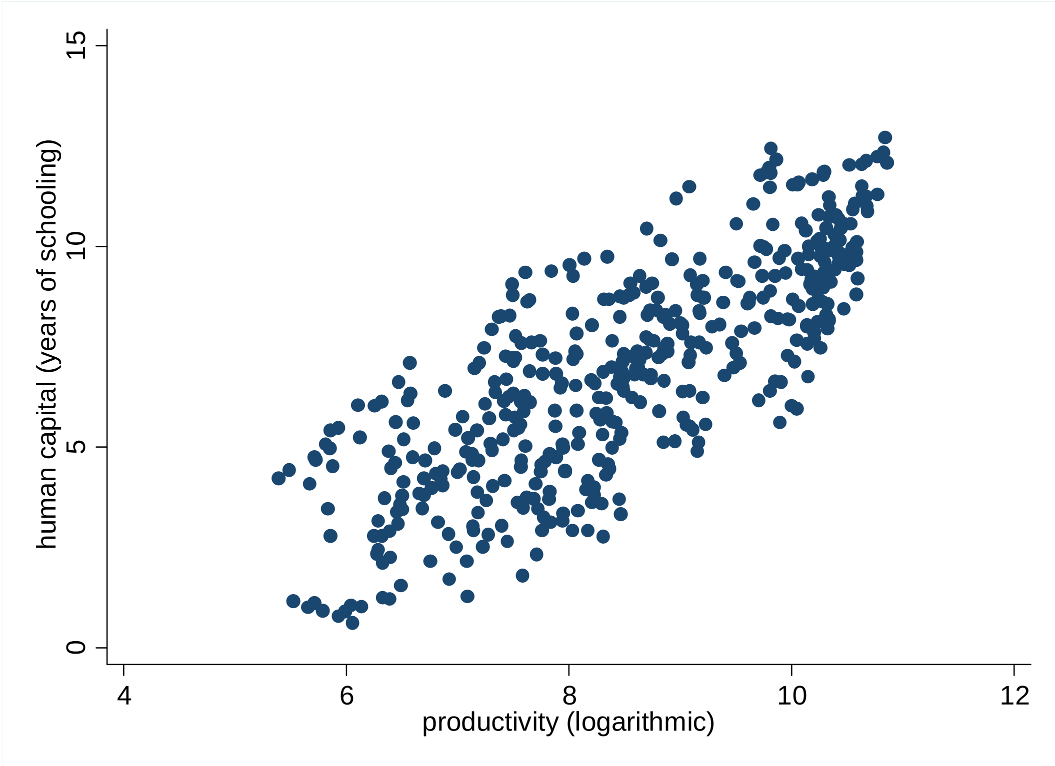
Most importantly, however, the model yields a positive and statistically highly significant coefficient for the catch-up variable $(\mathrm{H}_{\mathrm{i,t-1}} \cdot \mathrm{GAP}_{\mathrm{i,t-1}})$. The positive sign of the catch-up term's coefficient suggests that the growth effect from the technology gap is the greater the higher is the country's level of human capital.

The positive correlation between productivity and stocks of human capital, depicted in Figure 1, means that there is on the one hand a great potential for catching-up of countries with low productivity (high technology gap). On the other hand, the lack of human capital (absorptive capacity) may significantly reduce the strength of such a catch-up process or even prevent it.

Since the catch-up variable in specification (3) is an interaction term, the effect of the technology gap on GDP growth is non-linear (depending on the level of human capital) and cannot be read directly from the coefficient of the catch-up variable which is estimated to be 0.07.

[5] This growth effect appears to be large but remember that we use 5-year periods.
[6] In the growth literature population or labour force typically does not have strong growth effects. This may have to do with the fact that much of the literature uses GDP per capita as dependent variable while our dependent variable is GDP.

Figure 1 Scatter between human capital and productivity across country sample (1980-2009)



The coefficient of the catch-up term implies that at the average level of human capital in the sample (6.7 years of schooling), the growth effect of a 1 unit change in the technology gap is about 0.41 percentage points (0.061(coefficient) x 6.7(average value of human capital) x 0.01(Δtechnology gap)). In comparison, with a human capital stock of 3.4 year – which corresponds to Cote d'Ivoire's stock in the period 2005-2009 – the growth effect of a 1 unit change in the technology gap is suggested to be about 0.21 percentage points while at New Zealand's human capital level (12 years) the growth effect may be in an order of 0.73 percentage points.

Moreover, we can use the results in specification (3) to calculate the effect of a unit change in the catch-up variable which would be at the average level of human capital (6.7 years) and the average technology gap (0.75), a 1 unit higher catch-up term is associated with a 0.31 percentage points higher growth rate.

The logic applied here to calculate the effect of the technology gap is in line with the interpretation of interaction effects. However, specification (3) is somewhat problematic from an econometric point of view because it does not include the technology gap. This is problematic because being one of the variables used for building the interaction variable, the technology gap should also be included in the model (see e.g. Jaccard and Turrisi, 2003). Therefore specification (4) presents a 'full' model which includes the technology gap next to the catch-up variable.

In this specification both the productivity gap is statistically highly significant. The catch-up term is also positive but it is not significant, implying that there is no additional effect of higher human capital on the growth effect of the technological spillovers. In this constellation it is advisable to drop the interaction term and include the technology gap only to measure the effect of spillovers on growth.

This is done in specification (5) where as expected a similarly large coefficient as in specification (4) is found. The size of the coefficient of the technology gap suggests that a 1% increase in the technology gap is associated with 0.84 percentage points higher GDP growth. Again, it should be noted that this large effect applies to 5-year growth rates. Of course, specification (5) does not capture the indirect effect of human capital on growth through technology spillovers. An alternative interpretation would be that the positive coefficient on the technology gap variable may just indicate that countries which are further away from the technological frontier tend to grow faster. The technology gap in specification (5) is in a way the counterpart of the initial income term in neoclassical growth regressions as these two variables are highly correlated. Neoclassical growth regressions à la Mankiw, Romer and Weil (1992) interpret the coefficient of the income variable as indicating out-of-steady-state-convergence of countries with the same technology. In contrast, in the endogeneous growth framework, the process of convergence is triggered by a catch-up in the productivity level of technologically backward countries. This is why we associate the coefficient of the technology gap in the econometric model with technological catching-up induced by international spillovers.[7]

Given the problems surrounding the catch-up term in the OLS regressions, we try to capture the indirect growth effect of human capital that works via international technology spillovers with another approach. This approach consists of estimating the spillover effects within a threshold regression framework.

5.2 Results from threshold regressions

We now turn to the estimation of catch-up effects using the threshold regression model presented in equation (4). As pointed out above the threshold model allows for non-linearities in the growth effects stemming from the productivity gap where we allow different effects for groups of countries which are distinguished by their human capital level. Relating this to the theory of technology clubs we would expect such threshold somewhere at the lower range of the distribution of human capital stocks. Such a threshold separates the sample into a

[7] For a discussion of different interpretation of growth regressions in the neo-classical growth framework and the endogenous growth framework see Klenow and Rodriguez-Clare (1997).

low and a high regime where we associate the low regime with the stagnation club.

Potentially we may also find further thresholds. In particular we may find a threshold which can be related to the separation of the imitation and the innovation club. Such a model with two thresholds, (λ_1) and (λ_2) corresponds to three distinct regimes with respect to the growth effect of the technology gap (θ_1, θ_2 and θ_3). Associating the low, the medium and the high regimes with the stagnation club, the imitation club and the innovation club we expect the highest growth effects from international spillovers for the group of the imitation group, i.e. the medium regime.

Note that the threshold (or thresholds) are not pre-determined but is (are) selected in the course of the estimation process by repeatedly estimating the model each time with the potential threshold set at a different level of human capital. In our case we estimate the model with thresholds at each percentile of the data within the 10^{th} and 90^{th} percentile of the data. The final threshold is found by comparing the explanatory power of the models and selecting the model with the lowest sum of squared errors[8].

The results from the threshold regression allowing for non-linearities in the technology gap variable is shown in Table 4.

Column (I.1) shows that the data suggests a first threshold at the 17^{th} percentile of the human capital values which corresponds to approximately 3.7 years of schooling. The coefficients of the productivity gap are positive for both the low and the high regime. This corresponds to the pattern we expected: the growth effects from spillovers for countries with human capital (absorptive capacity) above the threshold are higher than those for countries below the threshold. However, given that we associate the low regime with the stagnation club the growth effects for the countries of the low regime are still of considerable size.

[8] Once a threshold has been found its statistical significance can be tested this test implies testing the null hypothesis that the two coefficients are the same. Under this null hypothesis the threshold λ is not defined so that bootstrapping methods are recommended for obtaining p values for the likelihood ratio test.

Table 4: Threshold regression testing non-linearities in the catch-up effects

Dependent variable: Δ log GDP per capita *(Δ ln $Y_{i,t}$)*

Threshold variable: one period lagged human capital (*$H_{i,t-1}$*)

Variables	Threshold 1 (I.1)	Threshold 2 (I.2)
$\Delta \ln K_{i,t}$	0.443***	0.422***
	0.0628	0.064
$\Delta \ln L_{i,t}$	0.345**	0.386**
	0.169	0.168
$H_{i,t-1}$	-0.0163	-0.0114
	0.0113	0.0112
$GAP_{i,t-1}$ low regime	0.752***	0.794***
	0.146	0.136
$GAP_{i,t-1}$ medium regime		0.835***
		0.131
$GAP_{i,t-1}$ high regime	0.808***	0.769***
	0.141	0.136
constant	-0.386***	-0.431***
	0.139	0.132
F-stat	12.89	13.12
R^2	0.615	0.62
Threshold	3.743	8.401
Percentile	17	70
P-value	0.013	0
Obs.	380	380

Note: Estimated with STATA 11. All estimations include country fixed and time fixed effects. Robust standard errors are shown below the coefficients. ***, **, * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 4 also reports p-values which are derived from a likelihood test testing the hypothesis that the estimated coefficients obtained for the low and the high regime are the same. Hence the hypothesis to be tested is:

$$H_0\colon \theta_1 = \theta_2$$

where ϕ_1 and ϕ_2 are the estimated coefficients of the productivity gap term for the low and the high regime respectively. The null-hypothesis is tested by a likelihood ratio tests. This likelihood ratio test has the following form

$$F = i \cdot t \cdot \frac{RSS^{linear\ model} - RSS^{threshold\ model}}{RSS^{threshold\ model}}$$

where *F* is the value of the likelihood test, $RSS^{linear\ model}$ is the residual sum of squares from the linear model (i.e. the model without a threshold) and $RSS^{threshold\ model}$ is the residual sum of squares from the threshold model. The sample size is given by the number of countries, *i*, multiplied by the number of time periods, *t*.

For obtaining a test statistic for this likelihood test a bootstrap approach is employed. For this predicted values from the actual data are generated. These predicted values are used for the bootstrap procedure in which *i* times t fitted values are drawn (with replacement) from the sample containing the fitted values. These fitted values serve as dependent variables and are combined with the actual data for the explanatory variables. With this simulated data set both the threshold model and the linear model are estimated. As with the actual data, the likelihood ratios are calculated for these simulated data. This bootstrap procedure is repeated 1000 times.

The p-values reported in Table 4 are obtained by counting the number of cases where the value of the likelihood ratio test of the simulated ($F_{simulated}$) exceed the value of the likelihood ratio test of the actual data (F_{actual}):

$$p - value = \sum_{b=1}^{1000} \frac{t_b}{1000} \qquad with \quad \begin{array}{l} t_b = 1 \; if \; F_{simulated} > F_{actual} \\ t_b = 0 \;\; else \end{array}$$

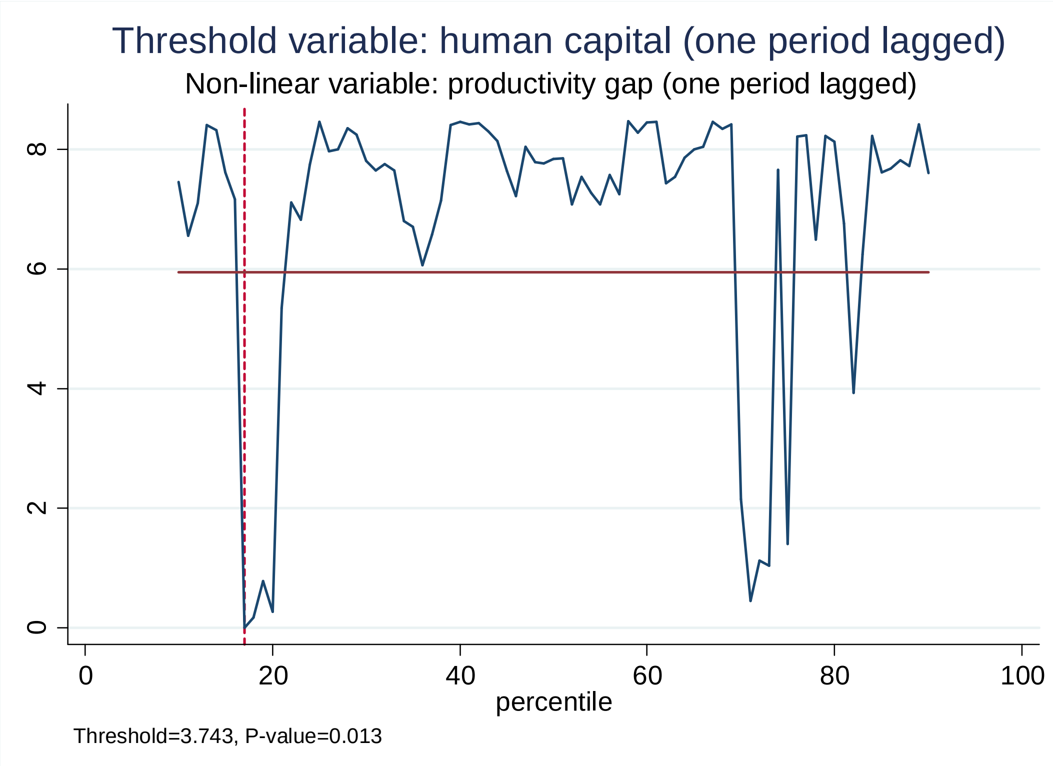
The p-value for the first threshold is 0.006 which implies that the estimated coefficients of the catch-up term are significantly different from each other even at the 1 percent level.

After the inspection of the estimated coefficients we may also check how precisely the threshold itself is estimated. The graph in Figure 2 shows likelihood ratios for models with alternative thresholds and the confidence intervals of the estimated threshold. The graph is obtained by performing a likelihood ratio test. This test consists of estimating equation (4) with the threshold imposed alternatively at each of the percentiles in the range of the 10^{th} to the 90^{th} percentile. In the actual likelihood test the residual sum of squares of the models with the alternative thresholds are compared with that of the threshold found in the estimation process. The horizontal line at the value of 5.94 is the critical value for the likelihood ratio at the 10% level of significance, provided by Hansen (2000). The graph in Figure 2 represents the likelihood ratio that results from the likelihood ratio test that compares the selected model with the model setting the threshold at the respective percentile. For all alternative models with likelihood values above this critical value of 5.94 we have a 90% probability that the fit of the selected model is significantly better, i.e. the alternative models have significantly larger residual sums of squares than the selected model. More precisely the likelihood ratio test for obtaining the confidence intervall has the following form

$$LR_p = i \cdot t \cdot \frac{RSS_p^{threshold\ model} - RSS_{selected}^{threshold\ model}}{RSS_{selected}^{threshold\ model}} \quad for\ all\ p \in [10{,}90]$$

where LR_p is the value of the likelihood ratio test with the threshold set at the p^{th} percentile of the data.

Figure 2 Likelihood ratio of the threshold



In our case the threshold at the 17th percentile is estimated rather precisely because both to the left and to the right of the 17th percentile the likelihood ratios of alternative models (i.e. models with the threshold at neighbouring percentiles) increase quickly and surpass the critical value in close vicinity of the 17th percentile. However, the confidence interval is very broad, reaching from shortly below the 20th percentile (where the graph and the line intersect the first time) to about the 75th percentile of the data. The reason for this very broad confidence interval is a drop in the likelihood ratio between the 70th and 80th percentile. This indicates that it is worth searching for an additional threshold.

The results from the threshold regression that allows for an additional threshold are reported in column (I.2) in Table 4.

The second threshold splits the sample of countries above 3.7 years of schooling into two further regimes (medium and high). The threshold is suggested to be at the 70th percentile corresponding to approximately 8.4 years of schooling. This results into a splitting of the sample into three distinct regimes. As can be seen the model finds the largest coefficient on the technology gap variable for the medium regime, amounting to 0.835. For the high regime, i.e. the countries with the highest level of human capital the coefficient is found to be considerably the lowest (0.769). In the two-threshold model (specification I.2) the coefficient for the low regime (stagnation club) is somewhat larger than in the one-threshold model, amounting to 0.794. As pointed out before, this is lower than for the imitation club but still rather high.

From the results of the threshold regressions we can conclude that countries with lower productivity tend to grow faster but that the extent to which countries can capitalise on their "advantages from backwardness" depends on their level of human capital. Below a certain threshold, countries reap lower growth effects from their productivity gap compared to the countries in the medium regime.

Hence, in line with the idea of technology clubs the countries with intermediate levels of human capital benefit most strongly from their technology gap in terms of the growth effect from spillovers. The members of the innovation club – according to our estimates – also benefit from technology spillovers though to a lesser extent than the imitation group. Contradicting the theory of technology clubs, however, is the fact that the third group, the countries with the lowest level of human capital, can still exploit their technology gap and benefit from spillovers, which does not really fit the idea of a stagnation club.

We read this result as clear evidence of non-linear effects from international spillovers, depending on the level of human capital. The principal pattern of these non-linear growth effects from spillovers do fit with the theoretical concept of technology clubs. However, the still considerable growth effects from international spillovers found for the countries with the lowest level of human capital is not reconcilable with the notion of a stagnation club.

6 Conclusions

In this paper we clustered countries into three distinct groups of countries on the basis of their innovative and absorptive capacities. In line with theoretical models of technology clubs we termed these clusters innovation club, imitation club and stagnation club. There are large differences in the mean values of the innovation and absorptive capacity (human capital) variables used in the cluster analysis. The differences are particularly pronounced in the human capital variable when comparing the stagnation and the imitation group. Along the R&D dimension the differences are larger between the innovation and the imitation groups.

In the growth regression framework we introduce the idea of technology clubs by letting the strength of the growth effect of the productivity gap vary with the level of human capital – our proxy for absorptive capacity. We do this by allowing for thresholds in the human capital variable. Hence, the threshold regression technique introduces the indirect growth effects of human capital which work through the absorption of technology spillovers by allowing different coefficients for the productivity gap term for different groups of countries. The thresholds that distinguish the country groups or clubs are determined by the data in the course of the estimation. The results from the threshold regressions suggest that the growth effects from international technology spillovers are strongest for countries with an intermediate level of human capital. Countries with very low levels of absorptive capacity benefit to a lesser extent from such catch-up effects but the growth effects are still considerable large. Too large in fact for arguing that this group of countries constitutes a stagnation club.

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Appendix

Table A1. List of countries in cluster analysis

WB code	Country	WB code	Country	WB code	country
AFG	Afghanistan	GUY	Guyana	NOR	Norway
ALB	Albania	HKG	Hong Kong SAR, China	NPL	Nepal
ARE	United Arab Emirates	HND	Honduras	NZL	New Zealand
ARG	Argentina	HRV	Croatia	PAK	Pakistan
ARM	Armenia	HTI	Haiti	PAN	Panama
AUS	Australia	HUN	Hungary	PER	Peru
AUT	Austria	IDN	Indonesia	PHL	Philippines
BDI	Burundi	IND	India	PNG	Papua New Guinea
BEL	Belgium	IRL	Ireland	POL	Poland
BEN	Benin	IRN	Iran, Islamic Rep.	PRT	Portugal
BGD	Bangladesh	IRQ	Iraq	PRY	Paraguay
BGR	Bulgaria	ISL	Iceland	QAT	Qatar
BHR	Bahrain	ITA	Italy	ROM	Romania
BLZ	Belize	JAM	Jamaica	RUS	Russian Federation
BOL	Bolivia	JOR	Jordan	RWA	Rwanda
BRA	Brazil	JPN	Japan	SAU	Saudi Arabia
BRB	Barbados	KAZ	Kazakhstan	SDN	Sudan
BWA	Botswana	KEN	Kenya	SEN	Senegal
CAF	Central African Republic	KGZ	Kyrgyz Republic	SGP	Singapore
CAN	Canada	KHM	Cambodia	SLE	Sierra Leone
CHE	Switzerland	KOR	Korea, Rep.	SLV	El Salvador
CHL	Chile	KWT	Kuwait	SRB	Serbia
CHN	China	LAO	Lao PDR	SVK	Slovak Republic
CIV	Cote d'Ivoire	LBR	Liberia	SVN	Slovenia
CMR	Cameroon	LBY	Libya	SWE	Sweden
COG	Congo, Rep.	LKA	Sri Lanka	SWZ	Swaziland
COL	Colombia	LSO	Lesotho	SYR	Syrian Arab Republic
CRI	Costa Rica	LTU	Lithuania	TGO	Togo
CUB	Cuba	LUX	Luxembourg	THA	Thailand
CYP	Cyprus	LVA	Latvia	TJK	Tajikistan
CZE	Czech Republic	MAC	Macao SAR, China	TON	Tonga
DEU	Germany	MAR	Morocco	TTO	Trinidad and Tobago
DNK	Denmark	MDA	Moldova	TUN	Tunisia
DOM	Dominican Republic	MDV	Maldives	TUR	Turkey
DZA	Algeria	MEX	Mexico	TZA	Tanzania
ECU	Ecuador	MLI	Mali	UGA	Uganda
EGY	Egypt, Arab Rep.	MLT	Malta	UKR	Ukraine
ESP	Spain	MMR	Myanmar	URY	Uruguay
EST	Estonia	MNG	Mongolia	USA	United States
FIN	Finland	MOZ	Mozambique	VEN	Venezuela, RB
FJI	Fiji	MRT	Mauritania	VNM	Vietnam
FRA	France	MUS	Mauritius	YEM	Yemen, Rep.
GAB	Gabon	MWI	Malawi	ZAF	South Africa
GBR	United Kingdom	MYS	Malaysia	ZAR	Congo, Dem. Rep.
GHA	Ghana	NAM	Namibia	ZMB	Zambia
GMB	Gambia, The	NER	Niger	ZWE	Zimbabwe
GRC	Greece	NIC	Nicaragua		
GTM	Guatemala	NLD	Netherlands		

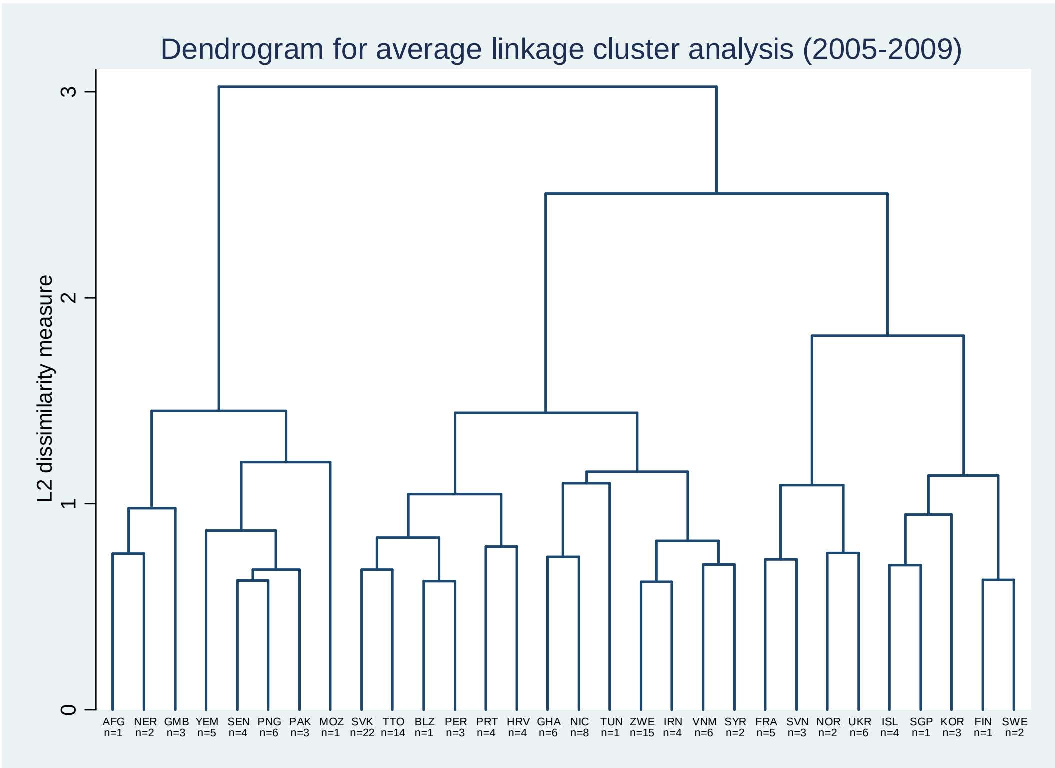
Table A2. List of countries in regression analysis

World Bank code	Country	World Bank code	Country
ARG	Argentina	ITA	Italy
AUS	Australia	JOR	Jordan
AUT	Austria	JPN	Japan
BEL	Belgium	KEN	Kenya
BGD	Bangladesh	KOR	Korea, Rep.
BGR	Bulgaria	LSO	Lesotho
BOL	Bolivia	MAR	Morocco
BRA	Brazil	MEX	Mexico
BWA	Botswana	MLI	Mali
CAN	Canada	MLT	Malta
CHE	Switzerland	MOZ	Mozambique
CHL	Chile	MUS	Mauritius
CHN	China	MYS	Malaysia
CIV	Cote d'Ivoire	NAM	Namibia
CMR	Cameroon	NIC	Nicaragua
CRI	Costa Rica	NLD	Netherlands
CUB	Cuba	NOR	Norway
CYP	Cyprus	NZL	New Zealand
DEU	Germany	PAK	Pakistan
DNK	Denmark	PAN	Panama
DZA	Algeria	PER	Peru
ECU	Ecuador	PHL	Philippines
EGY	Egypt, Arab Rep.	PRT	Portugal
ESP	Spain	PRY	Paraguay
FIN	Finland	SDN	Sudan
FRA	France	SEN	Senegal
GAB	Gabon	SLV	El Salvador
GBR	United Kingdom	SWE	Sweden
GRC	Greece	SWZ	Swaziland
GTM	Guatemala	SYR	Syrian Arab Republic
HKG	Hong Kong SAR, China	TGO	Togo
HND	Honduras	THA	Thailand
HUN	Hungary	TUN	Tunisia
IDN	Indonesia	URY	Uruguay
IND	India	USA	United States
IRL	Ireland	VEN	Venezuela, RB
IRN	Iran, Islamic Rep.	ZAF	South Africa
ISL	Iceland	ZMB	Zambia

Table A3. Pseudo-F values from Calinski-Harabasz method for determining the number of clusters

Number of clusters	Calinski/ Harabasz pseudo-F
2	102.74
3	166.89
4	140.82
5	117.70
6	175.53
7	149.05
8	157.73
9	145.53
10	131.96
11	131.05
12	140.45
13	133.67
14	129.31
15	129.98

Figure A1. Dendrogram for average linkage cluster analysis (2005-2009)



Note: Only upper part of cluster tree is shown.

Table A4. Pseudo-F values from Calinski-Harabasz method from non-hierarchical cluster analysis with alternative numbers of resulting clusters

Number of clusters	Calinski/ Harabasz pseudo-F
3	200.52
4	201.76
5	191.92
6	168.02