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Are North-South Technological Spillovers Substantial?

A dynamic panel data model estimation

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Abstract

This paper argues that *actual* technological spillovers are not substantial in developing countries because of the absence of an absorptive capacity. We carry out a panel data analysis in an attempt to gain insight into the specific aspects that enable economies to benefit from the backlog of existing knowledge. Our findings indicate that low productivity effects of human capital coupled with weak or virtually inexistent systems of innovation are at the root of the observed ambiguity with regard to the spillovers gains that are expected to play a significant role in sparking growth.

Keywords: absorptive capacity, spillovers, developing countries, systems of innovation

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I. Introduction

Amongst developing countries, there is a growing rift between the few economies that have managed to “take-off” and the overwhelming majority that is increasingly being marginalised by the current economic trend of rapid transformations. From a more general perspective, there is a great deal of evidence against the inevitable convergence predicted by earlier models, Solow (1956). Temple (1999) points out that, *“Poor countries are not catching up with the rich, and to some extent the international income distribution is becoming polarized.”* This situation has arisen with technology taking the centre stage in driving economies and modifying dynamics in the global economy. The question we address in this paper is: What lies behind the ability of a handful of developing countries to catch up with industrialised countries while the vast majority recedes further into marginalisation?

Technology led growth is characterised by rapid changes, due to pressure from such factors as rapid technical change and liberalisation, and evidence suggests that the returns to human capital are increasing, resulting in skill-biased technical change. However, the primary focus of classical, neoclassical and endogenous growth theory remains the allocation of scarce resources, consequently occulting structural feedback mechanisms that determine the dynamism of linkages and synergies in a rapidly changing environment. The national systems of innovation is an alternative approach proposed within the evolutionary technical change framework.

Pioneered and elaborated by Nelson & Winter (1982), Rosenberg (1986), Freeman (1987) among others, the national systems of innovation approach emphasises that the innovation process is a process of interactive learning in which actors improve their competences.[2] The

[2] Nelson & Winter (1982) articulated the evolutionary theory of firms and markets, Rosenberg (1988) the chain linked model as an alternative to the linear model and Freeman (1987) empirical findings.

endogenous structural, institutional and social factors, which constitute the so-called technological gap, have been stressed within the systems of innovation approach as largely responsible for driving economies apart. The underlying fact is that rapid economic transformations render competence acquisition increasingly tacit, and hence the importance of an adequate system of networks and linkages between and amongst research institutes, firms and the government in an economic system. This reflects the important role of economic structures and institutions in determining the rate and direction of innovative activities.

This paper attempts to show how the wide divergence amongst economies is mirrored by the rate of growth of knowledge, and that it reflects structural, institutional and social factors. More specifically, we argue that domestic innovation in developing countries is a vital source of sustainable growth despite the popular view that importing high technology equipment is the best way or even the only way to ignite growth in developing countries, and especially in the poorest, since they hardly invest in domestic R&D and innovation systems are virtually inexistent. Domestic innovation creates domestic technological capacities and capabilities, which increase the potential for technical progress through the interdependent process of domestic knowledge creation and the development of an absorptive capacity, and thus provides a solid basis for growth: the economic dynamism created by local innovation forms the basis for knowledge assimilation without which foreign technology cannot be absorbed and successful take-off that leads to catching up cannot take place.

Our argument is supported by the observations made by economist of technical change regarding the dual role of innovative activities. For example, Cohen & Levinthal (1989) argue that *"while R&D obviously generates innovations, it also develops the firm's ability to identify, assimilate, and exploit knowledge from the environment."* They further qualify this argument in which they postulate that *"firms conduct basic research less for particular results than to be able to provide themselves with the general background knowledge that would permit them to exploit rapidly useful scientific and technological knowledge…"*, Cohen & Levinthal (1990). Basic research broadens the knowledge base to create a critical overlap with new knowledge. In a similar vein, Abramovitz (1986) suggests that technical congruence is one of the elements that support the capacity of followers to exploit existing knowledge.

Foreign R&D is often considered as the main means of acquiring technology, and an analysis of north-south spillovers has led to a heated debate. Substantial economic literature propounds that technological growth in developing countries depends on foreign technology acquired through international transfer of technology, and as a result technology diffuses from the north to the south resulting in a reduction of the technology gap over time. For example, Coe, Helpman & Hoiffmaister (1997) empirically examine the extent to which developing countries, which hardly investment in their own R&D benefit from R&D performed in industrialised countries, and conclude that spillovers from the north to the south are substantial. Such contentions have been met with resistance in view of the fact that foreign R&D cannot on its own revamp systems of innovation: it appears unlikely that foreign technology may have much impact in the absence of an absorptive capacity. Indeed, the capacity to benefit from foreign technology appears to depend on the systems of innovation whose development relies largely on domestic innovation rather than on foreign technology.

An avalanche of empirical studies indicating that technology diffusion from industrialised countries has stronger effects in relatively rich countries than in poorer ones reinforces this point, Eaton & Kortum (1996), Xu (2000) and Keller (2001d). It is more probable that development of an absorptive capacity - which implies the need to focus on investment in domestic R&D, and human capital development as well as reinforcement of networks and linkages in the case of poorer developing countries - is paramount for productivity growth. In our paper, we show that domestic innovation lies at the core of the technology gap and is key to shrinking income differences over time.

Traditionally the concept of absorptive capacity has been associated with R&D activities in firms. Recent literature has broadened it to relate to the competence building in a rapidly changing economy as well as to include larger entities such as industrial districts, countries and regions. We note that innovation that arises from R&D is not the autonomous determinant of technical change: incremental transformations are responsible for the bulk of technological knowledge. In our analysis, domestic innovation in developing countries specifically relates to innovative activities based mainly on incremental knowledge. We define variables that relate to innovative activities, and in particular to technological knowledge dynamism at an economy level and then analyse their trends across groups of developing countries. The aim is to map out countries' ability to establish technological learning systems, and hence, to create technological knowledge that leads to technical progress.

We use the approach that consists in viewing total factor productivity as a residual in the production function. The residual is obtained by computing the ratio of national income to factors of production in a model that relates output to factor inputs, and a relationship between total factor productivity growth and both domestic and foreign knowledge is established in the next section. Section III discusses the estimation procedure of our dynamic panel data model and results of the estimation are presented in section IV. Alternative ways of determining domestic knowledge are discussed in section V. The last section concludes.

II. The model

We base our analysis on the approach introduced in the 1950's that views the residual of a Cobb-Douglas aggregate production function as the technology component.

$$Y = AF(K, H, L) \qquad \textbf{1}$$

Output Y depends on technology A, physical capital K, human capital H and labour L. One way of increasing output consists in increasing labour and/or investing in physical and human capital. However, growth of output ultimately yields to diminishing returns. The second way requires the improvement of the efficiency with which factor inputs are used i.e. improving technology A, and it results in sustainable growth.

In his estimates on productivity growth in the US economy, Solow (1957) found that technical change accounted for 80% of per capita growth while capital accumulation accounted for the remaining 20%. Easterly and Levine (2002) also found that technology, other than that incorporated in inputs, plays a fundamental role in growth. Technology or that 'something else' (as they termed it) that determines growth constituted two thirds of output while inputs accounted for only one third. Our study focuses on this technology term A.

We consider that the technological knowledge A is the component that permits countries to trigger off and maintain sustainable growth because it leads to an increase in output per unit input. Changes in the productivity of production processes are usually measured by variations in total factor productivity, the efficiency with which factor inputs are used. Cross-country differences in total factor productivity reflect differences in technology level. Total factor productivity is thus taken as a measure for the contribution of technical change to growth Kaldor (1957).[3]

Measurement of total factor productivity

We use a production function approach to relate total factor productivity to domestic and foreign innovation efforts. A Cobb-Douglas specification for aggregate production appears appropriate in the determination of total factor productivity since the rates of return to factor inputs form constant proportions of national income over time, which is one of stylised facts of economic growth, Kaldor (1961).

Mankiw, Romer & Weil (1992) integrate human capital in the textbook Solow growth model, which assumes a Cobb-Douglas production function. The resulting so-called "Augmented Solow model" takes the time spent in school as a measure of human capital investment. However, their integration of schooling in the Cobb-Douglas specification for aggregate production has a drawback: the rate of return to schooling is inversely proportional to years of schooling in the workforce, consequently implying high returns to schooling in countries with low stocks of education. Bloom et al (2004) note that in microeconomic studies, returns to education are found to be constant across countries, but no systematic variations of returns to schooling with income or years of schooling of the workforce are observed.

We adopt a standard production function in which aggregate production results from physical capital and human capital adjusted labour inputs,

[3] In growth accounting, an index that combines all measurable inputs is estimated and used to measure the rate of growth of national income i.e. to measure total factor productivity. However, a fundamental difficulty in modelling total factor productivity is that no independent measure for it exists.

$$Y_{it} = AK_{it}^{\alpha}\left(e^{\phi s}L_{it}\right)^{1-\alpha} \qquad \textbf{2}$$

$$where \quad e^{\phi s}L_{it} = hL_{it} = H_{it}$$

Y is the output, A is technology, K is physical capital, H is human capital (skilled labour) which is produced from raw labour (unskilled labour) L by means of education, and where s represents the average time spent in school (it is the ratio of total time spent in school to total labour force and is taken to be a proxy for human capital investment), while ϕ is the natural rate of return to schooling. Human capital is a simple Mincerian function of schooling.[4] The subscripts i and t denote country and time respectively.

The parameters of the production function are represented by α and $(1-\alpha)$. Each factor earns its marginal product so that α is the share of national income that goes to capital while $(1-\alpha)$ is the share of national income that goes to wages of the labour force. The total wage payments $(1-\alpha)Y$ do not distinguish between returns to raw labour and returns to schooling. The marginal product of an extra year of schooling is ϕY while the marginal product of a worker is $\frac{(1-\alpha)Y}{L}$.

[4]. Klenow & Rodriguez-Clare (2004) note that although a more complete Mincerian formulation would include years of experience in addition to schooling, taking experience into account has little effect on aggregate levels and growth rates. We therefore adopt the schooling only view of human capital production.

In the analysis, it is assumed that an extra year of schooling adds proportionately to output regardless of the level of schooling of the worker obtaining an extra year of schooling.[5] The marginal benefit of an extra year of schooling is the same for all workers regardless of the time spent in school by an individual worker.[6]

We suppose that the log of output per labour unit i depends on log capital per worker (capital intensity) plus log of human capital intensity and other factors captured in the residual. Dividing both sides of the specified aggregate production function by labour, taking the logs and dropping the indices for simplicity yields,

$$\log(Y/L) = \log A + \alpha \log(K/L) + (1-\alpha)\log\left(e^{\phi s} L/L\right) \qquad \textbf{3}$$

[5] The effect of schooling on the wages of an individual has been analysed based on the work of Mincer (1974) where a semi-log equation is used to demonstrate that returns to schooling are constant across countries: $\log W_j = \alpha_0 + \alpha_1 S_j$ where W_j is the wage of an individual j, and S_j his years of schooling. An extra year of schooling increases wages by the amount $\alpha_1 W_j$. The rate of return to schooling α_1 is taken to be the same for each worker regardless of the time spent in school by the individual. The wage equation suggests that returns to uneducated workers α_0 do not depend on the level of schooling in the workforce, Bloom et al (2004). This problem does not appear in the aggregate production function proposed as it is specified in such a way that the wage of an uneducated worker depends on the average level of education.

[6] However, the formulation of aggregate production that we adopt may lead to the implication that the rate of return to schooling is equivalent to the social rate of return of a worker. Bloom et al (2002), propose the formulation $Y_{it} = AK_{it}^{\alpha} e^{\phi s} L_{it}^{1-\alpha} \quad where \quad e^{\phi s} L_{it} = H_{it}$, which implies that the social rate of return for an average worker is $\frac{\phi}{(1-\alpha)}$. It can be demonstrated, nonetheless, that different workers face different social rates of return to schooling, $\frac{\phi}{(1-\alpha)+\phi(s_j - s)}$ where s_j is the number of years of schooling of a worker j, while s is the average years of schooling in the labour force. This is a limitation that occurs in any aggregate production that depends only on average (total) years of schooling as it makes the assumption that the marginal benefit is the same for all workers regardless of level of schooling, while the cost of schooling takes into consideration the education level of each worker in determining the output forgone by withdrawing a worker from the labour force. An aggregate production function that maintains the Mincer equation property, that the rate of return to education is the same for all workers should include distribution as well as the average level of human capital. In the interest of simplicity, we follow Bloom et al (2002) and assume that only the total stock of education matters and not its distribution.

Extracting total factor productivity and using lower case notation to indicate logs yields,

$$p_{it} = y_{it} - \alpha k_{it} - (1-\alpha)\phi s_{it} \qquad \textbf{4}$$

where $\log A$ is represented by p_{it}.

Analysis of total factor productivity growth

We relate total factor productivity to both foreign and domestic knowledge. This production function approach is one of the main methods used in analysing the impact of foreign knowledge on domestic productivity in a regression framework.[7] Economic literature identifies four sources that contribute to the improvement of productivity; domestic sources on the one hand that include domestic R&D and outward FDI, and foreign sources on the other hand which are made up of foreign R&D (via imports and partnerships/licensing) and inward FDI.

Improvement of total factor productivity is a process that results from learning and innovation efforts of both domestic and foreign firms. As noted earlier, innovation efforts by domestic firms lead to the creation of an absorptive capacity without which foreign technology is not likely to benefit domestic economies. We recall that an absorptive capacity refers to the ability to improve productivity through the adoption and application of foreign knowledge. Thus, domestic innovative efforts boost the learning capability that is critical for take-off and subsequent catch-up, which requires foreign knowledge.

[7] See for example Coe & Helpman (1995), Mohnen (2001)

In the absence of domestic sources of knowledge, particularly domestic innovation which normally precedes outward FDI, direct attempts to inject foreign knowledge (through, for example, high-technology content goods) are bound to penalise the learning process that leads to knowledge accumulation by provoking a fall in labour productivity. Furthermore, to a large extent foreign knowledge is induced by the presence of an absorptive capacity: the absence of an absorptive capacity, which reflects a weak learning process, inhibits foreign knowledge diffusion into domestic economies.

The implication here is that omission of domestic sources of knowledge from the estimation, as is often the case in empirical studies dealing with developing countries whose domestic innovation efforts are feeble while outward FDI is practically non-existent, may lead to bias of estimates as we shall discuss later in more detail.

Foreign R&D

We assume that foreign knowledge resulting from R&D efforts is transmitted to developing countries through imports of high technology content capital goods. v_{it}^{M} captures the real R&D intensity embodied in imports following Lichtenberge & van Pottleberghe de la Potterie (1996). An argument is put forward regarding the effect of foreign R&D capital stock on developing countries as occurring primarily and perhaps entirely through the indirect channel of trade since licensing/partnerships are almost exclusively amongst industrialised countries. Thus foreign R&D capital stock of a country i is represented by

$$v_i^M = \sum_j \left(v_j^d / y_j \right) m_{ij} \qquad \textbf{5}$$

where i and j represent the developing country and the industrialised country indexes respectively, v_j^d represents the domestic R&D capital stock of the industrialised country j, m_{ij} is the total imports of the developing country i from the industrialised country j, and y_j represents the GDP of the industrialised country j. The R&D intensity in the industrialised country is represented by v_j^d / y_j , but since we take the same group of industrialised as the trade partners for developing countries, the R&D intensity of industrialised countries is a constant term that may be eliminated from the equation.[8]

Inward FDI

Foreign knowledge embodied in inward FDI is computed to capture the intensity of foreign R&D in inward FDI. Thus,

$$v_i^{FDI} = \sum_j s_{ij} \left(v_j^d / k_j \right) \qquad \textbf{\textit{6}}$$

where s_{ij} is the inward FDI flows of the developing country i emanating from the industrialised country j, while v_j^d represents the domestic R&D capital stock of industrialised country j, and k_j is the capital stock of the industrialised country j. The R&D intensity of capital stock of industrialised countries may be interpreted as a constant and, therefore, eliminated from the equation since we maintain the same group of industrialised countries.

[8] The group of industrialised countries is indicated in appendix 1.

Domestic knowledge

While domestic innovation via both domestic R&D and outward FDI, has been found to play a critical role in productivity growth, particularly with regard to studies on industrialised countries, most empirical studies on developing countries do not account for it. The argument put forward is that developing countries' domestic innovation is insignificant and worse still, data is unavailable. Although this argument may be somewhat valid, we consider that the inclusion of a variable in the estimation specification reflecting the insignificance of domestic innovation is crucial.

To the extent that domestic innovation creates technological knowledge that is instrumental in the initial creation of an absorptive capacity, which has been identified as the element responsible for take-off and catch-up, it may be interesting to identify a variable that relates to the absorptive capacity. Such a variable would enable us to gain some understanding of why some countries are unable to take-off, and in some cases recede further into marginalisation.

We note that building-up of the learning capability, which allows the creation of an absorptive capacity, must take place during the pre-catching-up phase if take-off is expected to occur; as suggested by Cohen & Levinthal (1990) prior knowledge, which at the most elementary level includes basic skills, is the foundation for the 'initial' absorptive capacity. We assume therefore, that the learning capability fundamentally determines the creation and development of an initial stock of knowledge that triggers the cumulative and interactive process between knowledge stock and absorptive capacity, and thus sparks take-off.

In more general terms, the creation of a prior technological knowledge is closely tied to human capital development. Creation of knowledge arises from a variety of sources such as formal education, vocational training, in-firm training, learning on the job, and specialised employee training outside the firm, Lall (2000). The nature of formal education and vocational training in the economy determines the level of sophistication in the technologies employed. Modern technology requires fairly high levels and broad coverage of formal education and training. Hence, in-firm training, on the job learning, and specialised employee training outside the firm are calibrated on the base of formal education and training available in the economy.

Indeed, economic literature argues that human capital contributes to production directly (marginal product) and indirectly by inducing foreign knowledge - via capital imports of high technology contents, inward FDI, and licensing (in the case of industrialised countries) - and facilitating its use resulting in enhanced productivity growth. The indirect mechanism relies on competence creation, which occurs via domestic innovation, and as we saw domestic innovation is knowledge intensive and, hence, thrives upon human capital, Romer (1990). The productivity enhancing effect of human capital is increasingly identified as the link between education and growth: education policies oriented towards requirements in the business sector play a determinant role in economic performance. Hence, human capital is critical in an estimation specification explaining productivity growth.

A term relating the effects of human capital on productivity with the technological distance from the frontier appears relevant in our estimation specification. Since we are more interested in the indirect rather than direct effect of human capital on productivity in the definition of this variable, it is perhaps more interesting to interact it with a term that relates to the efficiency level, which in our case we refer to as the distance to the technological distance frontier: an estimation specification with an interaction coefficient may provide more accurate results.

The distance from the technological frontier, sometimes referred to as backwardness, may be viewed as the efficiency level of a country, which reflects the "quality" of the innovation system defined to include economic, social and political infrastructures and institutions. This would probably give a more accurate specification and perhaps remedy the problem of variable omission that ultimately leads to bias of estimates. Measurement of the "quality" of the innovation system or the efficiency level is a main concern.

One way in which empirical literature resolves this measurement problem consists in using the GDP ratio of machinery equipment imports to reflect the technological distance of a country from the frontier, Mayer (2001), Coe et al (1997). We note that the term obtained from interacting the GDP ratio of machinery equipment imports with human capital mirrors to some extent the absorptive capacity of country: the larger the ratio, the greater the indirect effect of human capital, which implies a greater capacity to reach the technology frontier through the cumulative and interactive process between knowledge stock and the capacity to assimilate foreign knowledge.

III. Estimation[9]

Our estimation specification is defined as a state dependent model,

$$p_{it} = \varphi p_{it-1} + \beta_1 v_{it}^{M} + \beta_2 v_{it}^{FDI} + \beta_3 v_{it}^{D} + \lambda_t + \mu_i + \omega_{it} \qquad 7$$

[9] See appendix 1 for data sources, data analysis and computation of capital stock.

where the total factor productivity is denoted by p_{it}, the lagged dependent variable by p_{it-1}, foreign R&D by v_{it}^{M}, inward FDI by v_{it}^{FDI}, and domestic knowledge v_{it}^{D}. Ideally, the domestic knowledge variable should be represented by domestic R&D and outward FDI. We assume that developing countries do not engage in these two activities or do so at an insignificant level and that data is unavailable. In our estimation we replace domestic knowledge v_{it}^{D} with an interaction term between human capital and the efficiency of production (GDP ratio of machinery and equipment imports as a proxy of production efficiency). We note that another way of estimating domestic knowledge v_{it}^{D} could be based on the "quality" of the systems of innovation inferred by the kalman filter. The country specific variable (representing for example geography) is denoted by μ_i, and λ_t denotes a time effect (captures the effect of the time variant technology frontier) such that $\lambda_{it} = \lambda_t + \nu_{it}$ where ν_{it} is included in the error term ω_{it}.

We emphasise that path dependence is a major factor influencing technology acquisition: it appears reasonable to assume that past productivity p_{it-1} influences current productivity p_{it}. In addition, past productivity may influence the other explanatory variables as discussed in the next subsection in greater detail. A dynamic model appears appropriate.

The standard methods that are used to estimate panel data models are fixed effects or random effects with the major difference between the two being the information utilised to calculate the coefficients: the fixed effect estimates are calculated from differences within each country across time and the method does not account for the presence of unobserved time invariant characteristics (it simply absorbs them into the fixed effects), while the random effects estimates incorporate information across individual countries as well as across periods.

Although the random effects estimates may be more efficient, the method requires that the country specific effects be uncorrelated with the explanatory variables for estimates to be consistent which is often unlikely. A Hausman specification test may to some extent be used to evaluate whether this independence assumption is satisfied.

Hausman & Taylor (1981) propose the use of an instrumental variables' estimation as a way to overcome the problem of bias in the estimates. Their approach entails transformation of the model to deviations from county means in order to get rid of the country specific effects that are correlated with the explanatory variables. The country mean deviations are used as instrumental variables to obtain consistent estimators.

However, even though the instrumental variable estimator is consistent it may not be efficient as correlation between the explanatory variables and the disturbance may still exist. Furthermore, the presence of a lagged dependent variable in our model makes the Hausman & Taylor approach inappropriate as it is not directly applicable to a dynamic model: the presence of a lagged dependent variable in the model violates the assumption of strict exogeneity as the lagged endogenous variable is bound to be correlated with the error term. In addition, since the time series dimension is fixed ($t = 21$ or $t = 5$ i.e. t does not approach infinity), the estimation is not consistent even as n goes to infinity. Hence, the bias for the coefficient of the lagged endogenous variable may be significant.

Arellano & Bond (1991) suggest an alternative estimation technique that corrects for the bias introduced by the lagged endogenous variable, and in addition, permits a certain degree of endogeneity in other regressors. We now discuss this method in more detail.

Effects of the absorptive capacity on productivity growth

We investigate the growth of total factor productivity using a sample of 51 developing countries over the period 1981- 2000.[10] The productivity growth equation:

$$p_{it} - p_{it-1} = (\varphi - 1)p_{it-1} + \beta_1 v_{it}^{M} + \beta_2 v_{it}^{FDI} + \beta_3 v_{it}^{D} + \lambda_t + \mu_i + \omega_{it} \qquad \textbf{\textit{8}}$$

may be rewritten as:

$$p_{it} = \varphi p_{it-1} + \beta_1 v_{it}^{M} + \beta_2 v_{it}^{FDI} + \beta_3 v_{it}^{D} + \lambda_t + \mu_i + \omega_{it} \qquad \textbf{\textit{9}}$$

The model holds for the years 1981 to 2000 with p_{i0} corresponding to 1980, the first year of data. It is assumed that one lag of the dependent variable, p_{it-1} is sufficient to capture the dynamics in the conditional expectation and any further lags on p_{it} or lags on the other explanatory variables are unimportant (inclusion of p_{it-1} in the model along with other explanatory variables is intended to control for another source of omitted variable bias).We need not restrict the value of φ since we are dealing with fixed time asymptotics. The coefficient of interest is on the domestic knowledge indicator v_{it}^{D} which captures the absorptive capacity of a country. We expect to obtain a robust and positive β_3.

One implication of the above model is that the lagged dependent variable is correlated with the disturbance (even if it is assumed that the disturbance itself is not autocorrelated) because of a possible bias by the individual specific effects since the same specific effect enters the equation for every observation in each group. $E(\omega_{it} \mid p_{it-1}) \neq 0 \quad t = 2,3,...T$ and estimation of

[10] See appendix 1 for country sample.

the model using the usual techniques would lead to an inconsistent estimator. Arellano and Bond propose an alternative estimation technique that corrects the bias introduced by the lagged dependent variable. The idea consists in first differencing the productivity growth equation

$$\begin{aligned} p_{it} - p_{it-1} = \varphi(p_{it-1} - p_{it-2}) + \beta_1\left(v_{it}^{M} - v_{it-1}^{M}\right) + \beta_2\left(v_{it}^{FDI} - v_{it-1}^{FDI}\right) \\ + \beta_3\left(v_{it}^{D} - v_{it-1}^{D}\right) + (\lambda_t - \lambda_{t-1}) + (\omega_{it} - \omega_{it-1}) \end{aligned} \qquad \textbf{\textit{10}}$$

equivalently

$$\Delta p_{it} = \theta_t + \varphi\, \Delta p_{it-1} + \beta_1 \Delta v_{it}^{M} + \beta_2 \Delta v_{it}^{FDI} + \beta_3 \Delta v_{it}^{D} + \Delta\omega_{it} \qquad \textbf{\textit{11}}$$

where time dummies are represented by $\theta_t = \lambda_t - \lambda_{t-1}$.

The first differencing transformation eliminates the country dummies (unobserved country effects) μ_i, and thus the bias introduced by the lagged dependent variable, and therefore allows the use of a simple instrumental variable estimator.[11] However, correlation between the lagged dependent variable and the disturbance still exists since past productivity influences the current level of foreign R&D spillovers, inward FDI and domestic knowledge: $V_{it} = \xi\, p_{it-1} + \alpha_t + \phi\, \mu_i + \varepsilon_{it}$ where $V_{it} \equiv \left(v_{it}^{M}, v_{it}^{FDI}, v_{it}^{D}\right)$. Lagged values of each of the independent variables are used as instruments so as to remedy the correlation problem between the explanatory variables and the disturbance $E\left(\omega_{it} \middle| V_{it}\right) \neq 0 \quad t = 1,2,3,\ldots T$.

$$E(V_{it}\omega_{is})\begin{cases} \neq 0 & s < t \\ = 0 & s > t \end{cases} \qquad V_{it} \text{ is predetermined and not strictly exogenous.}^{12}$$

[11] See appendix 2 for further details.

[12] We note that $E\left(p_{it} \middle| p_{it-1}, V_{it}, \theta_t\right)$ does not require that future exogenous variables be uncorrelated with disturbances: $E(V_{it}\omega_{is}) \neq 0 \quad \textit{for all} \quad s < t$ so that a feedback mechanism is allowed from p_{it} to V_{it+1}.

IV. Results

The table below reports estimates of the productivity growth equation using fixed effects, random effects, Hausman & Taylor procedure and the Arellano & Bond GMM technique. Estimates vary depending on the technique that is utilised making it necessary to test the validity of the assumptions underlying each method. First a Hausman specification test comparing the fixed-effects estimates in column [1] with the random effects in column [2] rejects the assumption that country specific effects are uncorrelated with the explanatory variables as is required for random effects. Nonetheless, both methods are inconsistent due to the presence of the lagged endogenous variable.

The coefficients of the Hausman & Taylor estimator reported in column [3] are virtually similar to those obtained by the fixed effects estimator in column [1] suggesting that specific effects do not bias the model and should therefore be included in the estimation equation. However, coefficients of the lagged dependent variables obtained by the Arellano & Bond approach used in column [4] are large and highly significant, suggesting that this method is preferable to the Hausman & Taylor technique used in column [3] whose estimates are inconsistent because it is also a static model (it does not take into account the lagged dependent variable). This is an informal way of selecting between the static and dynamic model since no formal test exists. It is noteworthy that although the presence of a lagged dependent variable points, *a fortiori*, to a dynamic rather than a static model, if the coefficients obtained in column [4] had not been robust this would have indicated the need to perhaps redefine the estimation specification i.e. a state dependent model would not have been appropriate.

However, the explanatory variable $V_{it} \equiv \left(v_{it}^{M}, v_{it}^{FDI}, v_{it}^{D}\right)$ must be predetermined by at least one period: $E\left(V_{it}\omega_{is}\right) = 0 \quad for\ all\ \ s > t$)

Estimates obtained using lagged instruments of the explanatory variables or regression of explanatory variables on the lagged dependent variable, suggest that past productivity influences the current level of the explanatory variables. For example, regressing foreign R&D spillovers on the lagged dependent variable suggests that past productivity influences the current level of foreign R&D spillovers i.e. $v_{it}^{M} = \xi p_{it-1} + \alpha_t + \phi \mu_i + \varepsilon_{it}$. This implies that $V_{it} \equiv \left(v_{it}^{M}, v_{it}^{FDI}, v_{it}^{D}\right)$ are predetermined by at least one period. Although endogeneity may exist between knowledge variables $V_{it} \equiv \left(v_{it}^{M}, v_{it}^{FDI}, v_{it}^{D}\right)$ and productivity growth, the test for autocorrelation and the Sargan test of over-identifying restrictions satisfy the underlying assumptions of the Arellano & Bond approach suggesting that estimates reported in column [4] are consistent and efficient.[13]

The coefficients of both the lagged dependent variable (lpdvty), and the foreign R&D variable (fkm) are positive and highly significant in all estimation techniques as expected. In addition, coefficients of the lagged dependent variable are fairly large, suggesting that past productivity plays a crucial role in future productivity.

[13] Although the Sargan test is satisfied, we note that one of its requirements is that the error terms must be homoscedastic whereas in our case they are heteroscedastic implying that the extent to which test can confirm the validity of instruments is limited.

REGRESSION RESULTS: ALTERNATE ESTIMATION TECHNIQUES

estimation method	Fixed effects	Random effects	Hausman & Taylor	Arellano & Bond	Arellano & Bond diff gmm	Arellano & Bond system gmm	Arellano & Bond system gmm
	period 1980-2000						5 five-year periods
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	pdvty	pdvty	pdvty	D.pdvty	pdvty	pdvty	pdvty
fkm	0.08	0.078	0.08		0.087	0.032	0.056
	(7.39)**	(7.45)**	(7.37)**		(7.92)**	(9.49)**	(3.08)**
fkfdi	-0.019	-0.018	-0.019		0.031	-0.002	0.025
	(3.28)**	(3.12)**	(3.27)**		(5.72)**	-0.76	-2
dk	-0.064	-0.061	-0.064		-0.008	-0.024	-0.05
	(5.40)**	(5.19)**	(5.39)**		(2.24)*	(7.07)**	(4.27)**
lpdvty					0.612	0.923	0.589
					(14.14)**	(47.95)**	(7.46)**
const	4.183	4.188	-7.439			0.148	1.35
	(69.37)**	(57.75)**	-0.03			-1.79	(4.21)**
LD.pdvty				0.845			
				(14.59)**			
D.fkm				0.05			
				(3.63)**			
D.fkfdi				0.013			
				-1.23			
D.dk				-0.008			
				-0.72			
ctry			0.383				
			-0.05				
obs	1071	1071	1071	969	969	1020	204
countries	51	51	51	51	51	51	51
R-squared	0.06						

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Table 1: Regression results

The variable representing foreign knowledge via FDI (fkfdi) gives mixed results in columns [4] to [7]. The original Arellano & Bond dynamic panel data estimator in column [4] reports a positive but insignificant coefficient. This result is improved by the Arellano & Bond “difference GMM estimator” in column [5], which is better than the original model because it provides a finite sample correction to the two-step covariance matrix that compensates for the severely down biased two-step estimates of the standard error, obtained in the original model. However, lagged levels in both the original Arellano & Bond estimator as well as the “difference GMM estimator” are usually poor instruments for the first differences, and especially for variables which are close to a random walk, which is the case in the explanatory variables of our model, and are therefore probably biased.

Indeed, the Arellano & Bond "system GMM estimator" in column [6], which is an augmented version of the "difference GMM estimator", does not confirm the result in column [5]. In the augmented version, original equations in levels are added so as to provide additional moment conditions that are used to increase the efficiency of the estimates. The "system GMM estimator" reports a negative coefficient, but it is not significant. We take a further step forward and remove "more developed" developing countries from the regression that we estimate for 5 five-year periods which implies that $t = 5$ instead of $t = 21$.[14] This mitigates the problem of loss of degrees of freedom. We obtain a negative and highly significant coefficient for foreign knowledge via FDI using the "system GMM estimator". A similar regression is carried out for the "more developed" developing countries. A positive and significant coefficient is obtained for this group of countries. These results appear particularly interesting and leads us to the conclusion that potential benefits of FDI accrue only to the small group of "more developed" developing countries that engage in domestic investment and thus, dispose of a relative absorptive capacity. Indeed, these are also the countries that would be able to attract market seeking FDI (horizontal FDI that is more pervasive in introducing foreign knowledge than vertical FDI), rather than serve as mere export platforms (vertical FDI).

This finally brings us to the coefficient of our main interest, domestic knowledge (dk), which gives the expected result: the coefficient is negative and highly significant in all estimation techniques except for the original Arellano & Bond estimator in column [4], which reports a non significant coefficient, while the Arellano & Bond "difference GMM estimator" reports a significance level of 5%. One interesting observation is that the coefficient remains negative throughout; it supports our initial view that although the commonly used interaction

[14] See appendix 2 for results of the two groups of developing countries.

coefficient between human capital and the GDP ratio of high technology imports may to some extent depict the absorptive capacity of a country it mainly portrays openness of an economy. This may lead to the conclusion that opening up fragile economies is likely to result in a negative effect on the productivity growth of these economies. Although economic research on the role of openness in developing countries has led to mixed results, a number of interesting papers including Fagerberg & Verspagen (2004) find that opening up weak economies is bad for growth. Indeed, efforts to inject foreign knowledge through for example high technology content imports are bound to penalise the learning process that leads to knowledge accumulation by provoking a fall in labour productivity. Devarajan, Easterly & Pack (2001) study on sub-Saharan Africa found no evidence of capital productivity which they concluded accounted for the low rates of investment in relation to other regions. In particular, their study on Tanzania revealed that constraints in skill acquisition were responsible for low capital productivity: increase in capital accumulation led to a fall in output per unit of labour and consequently a fall in output per unit of capital due to underutilisation.

It may be argued that the negative effect of domestic knowledge may represent technological backwardness or potential spillovers that provide an opportunity for catching-up as demonstrated in technology gap models, Fagerberg (1988). However, it would be reasonable to expect a negative coefficient for the whole sample of developing countries, including the "more developed" developing countries given that a technology gap still exists between them and the technology frontier. This group of countries still has the opportunity to benefit from potential technological spillovers from frontier economies.

V. Re-estimating domestic knowledge

In a bid to improve our analysis, it would be useful to attempt to capture the learning capability by resorting to a more innovative way of measuring the domestic knowledge variable. Since the "quality" of the systems of innovation is determined by a wide range of latent variables, the GDP ratio of machinery equipment imports may not quite reckon with these underlying factors because it appears to relate more to openness than to the absorptive capacity. The main aim of our estimation is to highlight the importance of creating an absorptive capacity – of domestic innovation – rather than to argue the case for north-south spillovers. Our argument is that north-south spillover benefits exist potentially and will accrue only if an absorptive capacity exists. Thus, the importance of the role of domestic knowledge creation, which includes building of a learning capability, in sparking take-off may be underestimated by specifying domestic knowledge as an interaction term between human capital and the GPD ratio of machinery equipment imports.

In developing countries where systems of innovation are relatively weak and in many cases wanting, the underlying factors that determine its "quality" may be best accounted for by adopting a broader view that makes it possible to at least capture the systemic character of innovation systems or the lack of them. The interest in capturing this systemic character lies in the fact that the factors constituting systems of innovation are embedded in what Abramovitz (1986) dubbed *'societal characteristics'* and purported that they are for a large part responsible for failure to achieve growth; systems of innovation are entrenched in historically evolved technical and cultural structures making it very difficult to change them, but at the same time they cannot be ignored as they are to a large extent responsible for driving economies apart because they determine the capacity to create knowledge.

Improvement of the quality of structural factors is a cumulative or sequential process and is therefore predetermined by the state of the existing structure. In addition, it supports an innovation process that is also cumulative in nature. Poor “quality” of the innovation system implies a country is backward while good “quality” is reflected by a small distance from the technology frontier. The “quality” of the systems of innovation may be assumed to mirror the efficiency of the domestic innovation process. We assume that the indirect effect of human capital, which may be interpreted as the learning capability, contributes to the “quality” of the systems of innovation, and may be seen as affecting the speed with which the domestic innovation process improves, leading to increased domestic knowledge.

The “quality” of innovation systems is a latent variable given that it is determined by latent factors, particularly domestic knowledge. The obvious problem we face here is that of measuring domestic knowledge, the variable of our concern. The Kalman filter approach that estimates the “state” of a linear system appears to offer a solution.[15] The technique may be used to obtain an estimator that gives an accurate estimate of the true state (domestic knowledge) even if we cannot measure it directly. Estimation of the dynamic panel data model using the inferred data may be carried out. In addition, the Kalman filter technique may be used to investigate the evolution of domestic knowledge with smooth changes, such that trend breaks to not appear do not appear as discontinuous events. Although this method has intuitive appeal it faces a drawback that would require cautious interpretations especially with regard to making projections into the future: inferring data in this manner is really an attempt to “squeeze the last drop of blood” out of the residue of the Cobb-Douglas function that is used as a proxy of the productivity variable in our estimation specification. A more interesting

[15] The Kalman filter is a set of mathematical functions that provides a means for recursively obtaining optimal estimates of past, present and future states of a process.

measure of domestic knowledge would require obtaining information outside the Cobb-Douglas function.

Information on domestic knowledge could alternatively be obtained using factor analysis. It can be used to capture, as comprehensibly as possible, the factors that may constitute domestic knowledge, while taking the necessary precautions in dealing with the limitations of the technique. The information would then be used to construct data for the domestic knowledge variable that would be used in the estimation of the dynamic panel data model. However, this work goes beyond the scope of this study particularly with regard to availability of data for a sufficiently large variety of indicators, and for our sample of 51 developing countries, as well as for our period of estimation (21 years). Nonetheless, this approach provides an interesting area of further research given that a direct measure of domestic innovation does not seem to exist, at least for the moment.

VI. Conclusion

Our results support the view that foreign knowledge generates a beneficial impact on the economic performance of the few developing countries that have been successful in embarking on an innovation-driven growth path by simultaneously engaging in technical competence creation and innovation, which both promote the process of knowledge accumulation; only those countries that invest in domestic innovation and develop an absorptive capacity benefit from international spillovers.

Estimation of the dynamic panel data model using the inferred data (kalman filter) for domestic knowledge may have provided an interesting basis for comparison with estimations that use the interaction coefficient between human capital and the GDP ratio of high technology imports as a proxy for domestic knowledge. However, we note that the explanatory power of linear models may be quite limited as concerns the absorptive capacity. The absorptive capacity is most probably represented by a sigmoid function, a functional form that approximates the stylised S-shaped function of technology diffusion models. A nonlinear logistic specification is much more likely to be robust. Benhabib & Spiegel (2002) estimation of a logistic specification reveals that divergence is a possible outcome for countries with no absorptive capacity.

To the extent that a solid technological infrastructure is indispensable for sustained growth, and that investment in knowledge producing activities may be scarce as is the case in most developing countries, there is a rational for public intervention with strong policy co-ordination that favours technological shifts. Admittedly, limited innovation may be caused by such factors as inadequate environment for risk taking, unavailability of information about technological opportunities, inadequate inputs (particularly competences), and taxation systems that fail to induce industrial activities.

Appendix 1

Country sample

Country list of 51 developing countries used in the analysis
(definition of developing countries is that of the WTO)

Africa (21 countries)	*Latin America (17 countries)*	*Asia (13 countries)*
Algeria	Argentina	Bangladesh
Benin	Bolivia	China
Cameroon	Brazil	Hong Kong
Central African Republic	Chile	India
Congo, Dem. Rep.	Colombia	Indonesia
Congo, Republic of	Costa Rica	Korea, Republic of
Egypt	Ecuador	Malaysia
Ghana	El Salvador	Nepal
Kenya	Guatemala	Pakistan
Malawi	Honduras	Philippines
Mali	Mexico	Singapore
Mauritius	Nicaragua	Sri Lanka
Mozambique	Panama	Thailand
Niger	Paraguay	
Rwanda	Peru	
Senegal	Uruguay	
Togo	Venezuela	
Tunisia		
Uganda		
Zambia		
Zimbabwe		

"more developed" developing countries (group one countries)	*other developing countries (group two countries)*	
Argentina	Algeria	Mauritius
Brazil	Bangladesh	Mozambique
Chile	Benin	Nepal
China	Bolivia	Nicaragua
Egypt	Cameroon	Niger
Hong Kong	Central African Republic	Panama
India	Colombia	Paraguay
Indonesia	Congo, Dem. Rep.	Peru
Korea, Republic of	Congo, Republic of	Philippines
Mexico	Costa Rica	Rwanda
Pakistan	Ecuador	Senegal
Singapore	El Salvador	Sri Lanka
Thailand	Ghana	Togo
Venezuela	Guatemala	Tunisia
	Honduras	Uganda
	Kenya	Uruguay
	Malawi	Zambia
	Malaysia	Zimbabwe

A sample of 22 advanced countries used in the analysis: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom, Australia, Canada, Japan, New Zealand, Norway, Switzerland, US.

Data

Capital stock

The initial physical capital stocks are calculated using the method proposed by Klenow & Rodriguez-Clare (1997)[16]

$$\frac{K}{Y}_{1980} = \frac{I_K / Y}{g + d + n} \tag{1}$$

where I_K / Y is the average investment rate in physical capital (1980-2000), g is an estimation of the world average growth rate of output per capita Y / L given as 0.02, d represents the rate of depreciation which is set at 0.03, and n is the rate of growth of the working population 15-64 year olds (1980-2000). The physical capital stock of a country i in period t satisfies as in Benhabib & Spiegel (1994).

$$K_{it} = \sum_{\varepsilon=0}^{t} (1-d)^{t-\varepsilon} I_{i\varepsilon} + (1-d)^t K_{1980} \tag{2}$$

Data for real income (PPP GDP), employment/labour (population) and PPP investment in physical capital are from the Penn World Tables version 6.1 (2002). Data for schooling, which is given as the average years of schooling in the population above 25 years of age, is obtained from Barro Lee data set (2000). The constant marginal rate of return to physical capital is set at $\alpha = 1/3$, and the rate of return to schooling $\phi = 0.085$ as described by Psacharopoulos & Patrinos (2002).

[16] A similar method is used by Bernanke & Gürkaynak (2001) where $K_{1980} = I_{1981} / (g + d)$ where *g* is the growth rate of output and *d* the rate of depreciation.

Foreign R&D

Data on machinery and transport equipment is obtained from the UN Comtrade database section 7 of SITC Rev. 2 from which we omit consumption goods as well as parts and components imported by developing countries for re-export after incorporation some form of value added. The analysis is based on mirror trade data: imports by developing countries are assumed to equivalent to exports by partner (industrialised) countries, due to the unavailability and unreliability of import data of most developing countries. The breakdown is as follows:

Machinery: SITC Rev. 2: 71-77 less 761-3, less 775-776

Transport & Equipment: SITC Rev. 2: 78-79

Inward FDI

Data is from UNCTAD Foreign Direct Investment Database (2004). The data base presents aggregate inward FDI stocks. We assume that the inward FDI stocks in developing countries emanating from the world rather than from the selected group of industrialised countries does not significantly alter results. In addition, we note that inward FDI may not constitute a significant channel through which knowledge is diffused: inward FDI may not contribute to the improvement of the host country's productivity since the foreign owner has no incentive to share technology and may prefer to adapt to the host country's technology. Indeed, inward FDI typically takes place via a wholly owned subsidiary in a bid to keep technology under the control of the multinational. [17]

[17] In their empirical study, Lichtenberge & van Pottleberghe de la Potterie (1996) found that inward FDI flows do not constitute a significant channel of technology transfer. While their study concerns industrialised countries there is reason to believe that the results would hold for developing countries.

Domestic knowledge

In our estimation, we begin by using the same approach in which we define as an interaction term between human capital and the GDP ratio of machinery equipment imports to represent the domestic knowledge variable of a country. The GDP ratio of machinery equipment imports is calculated using the UN Comtrade database section 7 of SITC Rev. 2 as described above and GDP from Penn World Tables while human capital data is obtained from Barro Lee 2000. The underlying condition in this approach, however, is that there exists an adequate level of human capital which brings us back to the importance of building what we referred to as a learning capability. In other words, direct attempts to inject foreign knowledge in economies that are poorly endowed in human capital may penalise the learning process that leads to knowledge accumulation by provoke a fall in labour productivity.

Appendix 2

Determination of instruments

The instruments are determined as follows:

For the period $t = 3$ the productivity equation may be written as:

$$p_{i3} - p_{i2} = \varphi\left(p_{i2} - p_{i1}\right) + \beta\left(V_{i3} - V_{i2}\right) + \theta_t + \left(\omega_{i3} - \omega_{i2}\right) \tag{1}$$

In the third period p_{i1} may serve as an instrument since it is highly correlated with $\left(p_{i2} - p_{i1}\right)$, but uncorrelated with $\left(\omega_{i3} - \omega_{i2}\right)$ if ω_{it} is a white noise. As for $\left(V_{i3} - V_{i2}\right)$, V_{i1} and V_{i2} are valid instruments since they are not correlated with the error term $\left(\omega_{i3} - \omega_{i2}\right)$. [Level instruments are preferable to difference instruments. Orthogonality conditions are stated in terms of the levels of the variables and the differences of the disturbances $E\left(V_{is}\Delta\omega_{it}\right) = 0$ as opposed to differences of both the variables and the disturbances $E\left(\Delta V_{is}\Delta\omega_{it}\right) = 0$ which is implied $s = 1,...,t-2$ Arellano (1989)]

The matrix of instruments may be written as:

$$Z_i = \begin{bmatrix} p_{i1}, V_{i1}, V_{i2} & d_{1982} & \cdots & \cdots & 0 & 0 \\ & & p_{i1}, p_{i2}, V_{i1}, V_{i2}, V_{i3} & d_{1983} & \vdots & \vdots \\ \vdots & \vdots & & \ddots & & \\ 0 & 0 & \cdots & \cdots & p_{i1},...p_{iT-2}, V_{i1},...V_{iT-1} & d_{2000} \end{bmatrix}$$

d_{year} represents the year specific dummy variable.

Once the instruments are identified the instrumental variables method is applied to the first differenced productivity equation

$$\Delta p_{it} = \theta_t + \varphi\, \Delta p_{it-1} + \beta \Delta V_{it} + \Delta\omega_{it} \tag{2}$$

Let $\begin{bmatrix} \varphi \\ \beta \end{bmatrix} = \delta$. A convergent estimator of the parameter δ is obtained but, the GMM estimator of δ may not be efficient since $(\omega_{it} - \omega_{it-1})$ is a random walk with a unit root:. $\omega_{it} - \omega_{it-1} = \Delta\omega_{it}$ hence, $\omega_{it} = \omega_{it-1} + \Delta\omega_{it}$ is a random walk since it is assumed that $\Delta\omega_{it}$ has no serial correlation (it is a white noise).

We assumed that the first difference of the idiosyncratic errors $\Delta\omega_{it} : t = 2,3,...T$ are serially uncorrelated and have constant variance.

$$E(w_i w_i' | p_{i0},...p_{iT-1}, V_{i1},...V_{iT}, \mu_i) = \sigma_w^2 I_{T-1}$$

where w_i is the $(T-1)\times 1$ vector containing $\Delta\omega_{it} : t = 2,3,...T$.

Since this assumption may not be verified $E(w_i w_i') \neq \sigma_w^2 I_{T-1}$ we use a matrix of instruments $Z = [Z_1',...Z_N']'$ such that the orthogonality conditions are now $E(Z_i'\Delta\omega_i) = 0$. This is the weakest assumption that can be imposed in a regression framework to get a consistent estimator of δ. Under this assumption the vector δ satisfies

$$E[Z'\Delta p - Z'(\ \Delta p_{-1}\Delta V)\delta] = E[Z'\Delta\omega] = 0$$

or equivalently

$$E\left[Z'\left(\ \Delta p_{-1}\Delta V\right)\delta\right]=E\left[Z'\Delta p\right]$$

where $Z'\Delta p$ is a $K\times 1$ random vector and $Z'\left(\ \Delta p_{-1}\Delta V\right)$ is a $K\times K$. To be able to estimate δ, we assume that it is the only $K\times 1$ vector that satisfies the orthogonality condition. This implies that although this orthogonality condition is the basis for estimating δ, the rank condition is required as a sufficient assumption for identification.

The assumption of a full rank implies that the system has a unique solution – there is no overidentification

$$rank\left(\sum_{t=2}^{T}E\left(\Delta X'_{it}\Delta X_{it}\right)\right)=K$$

$$\Delta X_{it}\equiv\left(\Delta p_{it-1},\Delta V_{it}\right)$$

Time constant explanatory variables and perfect collinearity among the time varying variables is ruled out. The matrix is non-singular, which rules out the presence of linear dependence.

Estimating δ

With the orthogonality conditions and the full rank assumption solving, for δ will yield a unique solution. We use a weighting matrix $\hat{W}$, a positive semi definite matrix, in the quadratic form to obtain $\hat{\delta}$.

$$\hat{\delta} = \min_{\delta}\left[\sum_{i=1}^{N} Z_i'\left(\Delta p_i - \Delta X_i \delta\right)\right]' \hat{W}\left[\sum_{i=1}^{N} Z_i'\left(\Delta p_i - \Delta X_i \delta\right)\right]$$

Hence, $\hat{\delta} = \dfrac{\Delta p Z'\hat{W}Z'\Delta p}{(\Delta p_{-1}\Delta V)Z'\hat{W}Z'(\Delta p_{-1}\Delta V)} = \left[(\Delta p_{-1}\Delta V)Z'\hat{W}Z'(\Delta p_{-1}\Delta V)\right]^{-1}\left[\Delta p Z'\hat{W}Z'\Delta p\right]$

First step

The first choice of the weighting matrix $\hat{W}$ is

$\hat{W} = \left(N^{-1}\sum_{i=1}^{N} Z_i' Z_i\right)^{-1}$ which is a consistent estimator of $\left[E\left(Z_i' Z_i\right)\right]^{-1}$

The IV estimator of δ may be written as:

$$\hat{\delta}_{IV} = \left(\left[\Delta p_{-1}\Delta V\right]' Z\left(Z_i' Z_i\right)^{-1} Z'\left[\Delta p_{-1}\Delta V\right]\right)^{-1}\left(\left[\Delta p_{-1}\Delta V\right]' Z\left(Z_i' Z_i\right)^{-1} Z'\Delta p\right) \tag{3}$$

The weighting matrix $\hat{W} = \left(\dfrac{1}{N}\sum_{i=1}^{N} Z_i' Z_i\right)^{-1}$ gives the initial consistent estimator $\hat{\delta}_1$, but may not be necessarily the asymptotically efficient estimator. However, it is important because we need a preliminary consistent estimator of δ to obtain the asymptotically efficient estimator.

Second step

The optimal weighting matrix that produces the GMM estimator with the smallest asymptotic variance is

$$\hat{W} = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \Delta\hat{\omega}\ \Delta\hat{\omega}' Z_i \right)^{-1}$$

The optimal GMM estimator of δ may be written as:

$$\hat{\delta}_{GMM} = \left(\left[\Delta p_{-1} \Delta V \right]' Z\hat{W}Z' \left[\Delta p_{-1} \Delta V \right] \right)^{-1} \left(\left[\Delta p_{-1} \Delta V \right]' Z\hat{W}Z' \Delta p \right) \tag{4}$$

Columns [8] and [9] distinguish between “more developed” (group one) and “less developed” (group two).developing countries

REGRESSION RESULTS: ALTERNATE ESTIMATION TECHNIQUES

	period 1980-2000						5 five year periods		
							Arellano & Bond system gmm		
estimation method	Fixed effects	Random effects	Hausman & Taylor	Arellano & Bond	Arellano & Bond diff gmm	Arellano & Bond system gmm	all countries	group two	group one
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	_	_	_	D.pdvty	pdvty	pdvty	pdvty	pdvty	pdvty
fkm	..	..	..		0.087	0.032	0.056	0.075	-0.001
	..	..	..		(7.92)**	(9.49)**	(3.08)**	(3.35)**	-0.09
fkfdi	..	..	..		0.031	-0.002	0.025	-0.056	0.037
	..	..	..		(5.72)**	-0.76	-2	(3.56)**	(2.25)*
dk	..	..	..		-0.008	-0.024	-0.05	-0.027	0.003
	..	..	..		(2.24)*	(7.07)**	(4.27)**	-1.21	-0.5
grp			..						
			..						
lpdvty					0.612	0.923	0.589	1.19	0.765
					(14.14)**	(47.95)**	(7.46)**	(11.54)**	(11.53)**
const	..	..	..			0.148	1.35	-1.076	0.783
	..	..	..			-1.79	(4.21)**	(2.56)*	(2.77)*
LD.pdvty				0.845					
				(14.59)**					
D.fkm				0.05					
				(3.63)**					
D.fkfdi				0.013					
				-1.23					
D.dk				-0.008					
				-0.72					
conti			..						
			..						
ctry			..						
			..						
obs	1071	1071	1071	969	969	1020	204	148	56
no. ctries	51	51	51	51	51	51	51	37	14

R-squared 0.06 Absolute value of t statistics in parentheses * significant at 5%; ** significar

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