TECHNOLOGY GAP, CATCHING-UP AND OUTWARD ORIENTATION:
ANALYSIS OF 63 COUNTRIES
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Abstract
This paper examines the determinants of technological catching-up across 63 countries over the period 1982-2000 using a two staged approach. In the first stage, a measure of the technology gap between countries and the global technology frontier is computed. A positive growth of this measure is interpreted as technological catching-up. In the second stage, technology gap and technological catching-up are regressed against trade openness, FDI inflows and FDI outflows, domestic R&D, and human capital. Two main findings emerge. First, technologically backward countries catch-up faster. Second, FDI inflows, trade openness and human capital have positive effects on closing the technology gap.

JEL Classification: C33, F02, O47, O57

Keywords: Metafrontier, technology gap, catching-up, absorptive capacity, foreign direct investment.

1. Introduction

Technological advancement has been increasingly seen as the principal driver for long term national prosperity. As this doctrine has taken roots, using public policy and funding to stimulate innovation are deemed not only desirable, but indeed indispensable if a country wants to maintain its global competitiveness. The need to design and, subsequently, evaluate any innovation policies has led to the search for methods to measure and compare technological capability across countries and over time. As a result, there has been a proliferation of works aiming at quantifying technological capability at the national level (see Grupp and Mogee (2004) for a brief survey).

There are two basic approaches to the measurement of technological capability of a country – the indicators approach and the modeling approach. The indicators approach involves the collection of a range of statistics that describe various aspects of innovation, such as the number of scientific publications and the expenditure on R&D. Examples include the Technology Achievement Index developed by the United Nations Development Program, the ArCo index (Archibugi and Coco 2003) and the Science & Technology Indicator by the OECD. Constructing such indicators will inevitably encounter problems in data collections, especially for developing countries, as well as in weighting and aggregating various incommensurable components (e.g. schooling and patents).

The modeling approach has been largely based on the framework of the Solow growth model and its endogenous growth descendants. Using growth accounting or econometric methods with aggregate data, the modeling approach circumvents many data related problems facing its indicators counterpart. This approach focuses on the change of

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technological capability (i.e. technological progress) rather than the actual level of the capability. Technological progress of countries is usually measured by total factor productivity (TFP) growth rates. Such a measure implicitly assumes TFP growth is predominantly, if not purely, a result of technological changes. However, both technological progress and efficiency improvement will lead to higher real output for given inputs. Failing to separate technological change and efficiency change will risk biasing the estimation of technological progress.

In this paper, we submit that the recently developed metafrontier technique offers an alternative approach to measure technological capability. The advantages of the metafrontier technique are that it is able to separate technological change from efficiency change and is also parsimonious in terms of data requirements. Specifically, the implementation of the metafrontier technique requires data only on output, capital stock and labour input. The technique involves constructing a global technology production frontier (or a metafrontier) and then separating the countries in the sample into relatively homogeneous groups and estimating group-specific frontiers. In the metafrontier framework, two measures of efficiency are obtained for each country each year: one vis-à-vis the group frontier and the other vis-à-vis the metafrontier. The ratio of the efficiencies, known as the metafrontier ratio (MFR), provides a measurement of the technology gap between a country and the metafrontier. Countries of a higher MFR are closer to the metafrontier and, hence, technologically more advanced. As a result, countries of a positive growth rate of the MFR are catching up technologically.

Another advantage of the metafrontier method is that a unique MFR measure can be computed for each country each year, providing a panel of measurements. These measures allow us to further investigate the determinants of the technological catching up process across countries and over time, which is the second aim of this paper. In particular, we investigate the effects of outward orientation, as typified by the scale of international trade and foreign direct investment (FDI), on technology gap and the catching-up process.

Theories of relative backwardness postulate that the larger the gap between a country’s technology and the global technology, the greater the potential for technological catching-up. Nonetheless, such potential can be tapped into only when there is adequate access to foreign technology because the source of new technology is typically foreign (Eaton and Kortum 1999). For a given level of technological backwardness, it can be argued that countries that are relatively open to foreign technology will enjoy a faster rate of technological catching up. This view finds support in the policy prescriptions of multilateral institutions such as the World Bank, the IMF and the OECD.

Trade and foreign direct investment (FDI) flows are commonly hypothesized as predominant channels of foreign technologies. However, most FDI studies using panel

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2 Metafrontier ratio was previously known as technology gap ratio.
3 We obtain a large panel of MFRs, comprising of 63 countries over the period 1982-2000, accounting for roughly 91 percent of the world’s output, 79 percent of trade and 91 percent of FDI respectively. Trade and FDI are two key variables in the analysis to be explained later.
4 This is based on the viewpoint that the level of technology is embodied in a country's capital stock. When a country replaces its old capital stock, the accompanying technological gains are restricted by the advancements in technology since the old stock was installed (Abramovitz 1989).
data have failed to find evidence of positive technology spillovers and few have even obtained evidence of negative spillovers (Görg and Greenaway 2004). Likewise, the empirical evidence on technological externalities from trade remains ambiguous (Nadiri and Kim 1996; Keller 1998). One potential and much neglected reason for the lack of consensus in the empirical literature evaluating the technology spillovers from trade and FDI is the absence of a measure of pure technology, i.e., devoid of inefficiency. Accordingly, with a new MFR measure that is free of the efficiency component, this study sets out to re-examine the determinants of technological catching-up. We conduct empirical analysis by regressing the obtained MFR against measures of trade openness, FDI inflows, FDI outflows, human capital and indigenous R&D. While the trade and FDI measures are included to accommodate the role of outward orientation, human capital and indigenous R&D are included to capture the effect of domestic variables. Including domestic variables ensures that the effects of outward orientation are not biased.

The remainder of the paper is structured as follows. The next section explains the two step methodology used in the paper, namely, the application of the metafrontier technique to measure the technological gap, and, the use of econometric models to study the role of international linkages in explaining technological gap and the catching-up process. Section 3 presents and discusses the empirical results. Section 4 concludes.

2. Methods

2.1 Measuring Technological Gap

The metafrontier technique provides a method for the computation of an ‘inefficiency free’ measure of technological gap, known as the metafrontier ratio (MFR), for the sample of countries. It is an extension of conventional frontier approaches such as data envelopment analysis (DEA) and stochastic frontier approach (SFA). It offers several improvements over the conventional approaches. Firstly, it does not assume a common technology for all the countries in the sample. Instead, only relatively homogeneous countries are grouped together and assumed to share a common technological frontier within the group. Secondly, the metafrontier technique offers a separate, time dependent technology gap measure for each country in the sample. This makes the measures derived from the metafrontier technique well suited for second stage panel regressions.

In this paper, the group frontiers and the associated efficiencies of the countries in each group are estimated using the usual SFA routines. In SFA, the form of the production function needs to be specified. We test a Cobb-Douglas functional form against a more flexible translog form. Further, we test three alternative time varying parameter specifications, namely, 1) intercept parameters are allowed to vary yearly, 2) intercept parameters are allowed to vary yearly and slope parameters are allowed to differ in blocks.

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5 For instance, in the case of FDI inflows, the source (foreign) firms might exercise monopolistic powers in the host countries, resulting in the contraction of domestic competitors, which could further lead to contraction of other forward and downward linking domestic productions.

6 It is known that the adequacy of the measures derived from conventional frontier techniques depends critically on the coverage of countries.

7 MFRs obtained using the DEA methodology are available from the authors on request.
of ten years, and 3) intercept parameters are allowed to vary yearly and slope parameters are allowed to differ in blocks of five years. These three specifications allow the group frontiers to accommodate non-neutral technological shifts. The metafrontier (or the global frontier) is an enveloping function estimated using the pooled data from all the groups. It can be estimated through either a parametric or a non-parametric approach.\textsuperscript{8} Here, the metafrontier is estimated using a parametric approach. The procedure is an extension of the traditional SFA and is explained in O’Donnell \textit{et al.}, (2008).

Since the metafrontier is an enveloping function, the metatechnology (the technology underlying the metafrontier) represents the totality of group-specific technologies.\textsuperscript{9} Thus, a measure of the gap between a particular country’s technology and the metatechnology is defined as a ratio of technical efficiencies.

\[ MFR_{it} = \frac{TEM_{it}}{TEG_{it}} \]  

where,

- \( MFR_{it} \) denotes the metafrontier ratio for country \( i \) at time period \( t \)
- \( TEM_{it} \) denotes the technical efficiency of country \( i \) with respect to the metafrontier at time period \( t \)
- \( TEG_{it} \) denotes the technical efficiency of country \( i \) with respect to its group frontier at time period \( t \).

The MFR indicates how far a country is from the world’s technology frontier. Suppose country \( i \) is sorted into the \( k \)-th group based on certain criteria. \( MFR_{it} \) measures the ratio of the potential output defined by the frontier production function for the \( k \)-th group relative to the potential output defined by the metafrontier function, given the observed input mix for country \( i \) at time period \( t \). For example, if \( TEG_{it} = 0.8 \) and \( TEM_{it} = 0.6 \), it means that country \( i \) is producing 80 percent of the potential output using the \( k \)-th group technology, but it would be producing only 60 per cent of the potential output should it be using the metatechnology. The efficiency reduces because the potential output rises with the metatechnology while the actual output remains the same. Therefore, country \( i \)’s metafrontier ratio is 0.75 (= 0.6/0.8). This means that, if the country were 100 percent efficient, the \( k \)-th group technology will allow it to produce only 75 percent of what it would do with the metatechnology. Thus, the metafrontier technique allows the computing, based on the distance between a country’s potential output level and the

\textsuperscript{8} The construction of the metafrontier surface requires that the estimated metaproduction function does not fall below the deterministic functions of the groups involved. This requires some constraining using linear programming (LP) when SFA is used to determine the group- and metafrontiers. The need for LP arises because the SFA accommodates random disturbances. If the DEA approach is used, the frontier determined by pooled data is already the metafrontier. This is because the DEA is a deterministic approach and consequently the metafrontier envelopes all the group frontiers.

\textsuperscript{9} Technology is defined as a state of knowledge in existence at a given point of time. The metafrontier or metatechnology satisfies all the necessary technology axioms (see O’Donnell \textit{et al.}, (2008) for a detailed discussion).
(hypothetical) technological leader’s potential output level for a given input mix, of a relative measure of technological advancement devoid of the inefficiency component. By construction, the MFR ranges from zero to one, a country that lies on the metafrontier will have a MFR equal to one. A higher value of MFR implies the country is closer to the global technological frontier and, therefore, a positive growth rate of MFR indicates that the country is catching-up with the technological leader.

Our grouping of countries is based on income level. The 63 countries in the sample are sorted into two income groups: low and middle income (G1), and high income (G2). G1 has 38 countries and G2 has 25. We do not divide them into more groups because it would render the number of observations in each group too small for the estimation of the group frontier. Appendix 1 lists the sample countries grouped by income. Each of these income groups has a specific technological frontier. Computing the MFR requires only aggregate output (real GDP) and factor input data. In this paper, capital stock and labor are modeled as factor inputs. The capital stocks are constructed from the Penn World Tables’ investment data using the perpetual inventory method and labor input is measured by the total labor force. See Appendix 2 for details on the construction and compilation of the dataset.

2.2. An Econometric Model of Catching-up

From the first stage, we obtain a large panel of MFRs, comprising of 63 countries over the period 1982-2000. In the second stage of the empirical analysis, the computed MFRs, are regressed against a host of explanatory variables in order to examine the determinants of technological gap. We explore two alternative forms of the model. First a model of the level of MFR is estimated. The MFR is bounded between zero and one, thus we estimate the model as a logit regression.\(^ {10}\)

\[
\ln \left[ \frac{MFR_{it}}{1 - MFR_{it}} \right] = \alpha_0 + \beta_1 TOP_{it} + \beta_2 HC_{it} + \beta_3 DRD_{it} + \beta_4 FDI_{it} + \beta_5 FDIO_{it} \\
+ \text{interaction terms} + \epsilon_i + \lambda_i + e_{it}
\]

(2)

Second a model of the MFR growth rate\(^ {11}\) is estimated:

\[
\frac{\sqrt{MFR_{it}}}{\sqrt{MFR_{i,t-1}}} = \alpha_0 + \beta_1 TOP_{it} + \beta_2 HC_{it} + \beta_3 DRD_{it} + \beta_4 FDI_{it} + \beta_5 FDIO_{it} \\
+ \text{interaction terms} + \epsilon_i + \lambda_i + e_{it}
\]

(3)

The choice of explanatory variables and their expected effects is explained below.

Summary statistics of the explained and explanatory variables are provided below:

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\(^{10}\) The approach is similar to that of estimating a model for proportions.

\(^{11}\) The growth rates are computed as \(\frac{\sqrt{MFR_{it}}}{\sqrt{MFR_{i,t-1}}} = (MFR_{it} - MFR_{i,t-1}) / MFR_{i,t-1} \). Full results for individual countries can be obtained from the authors.
Trade Openness (TOP)
Countries that are more open to international trade are expected to catch up faster than those that are relatively closed, as they can source more technology from their trading partners (Edwards 1998). Some studies tend to focus only on imports as a channel of technological spillovers (Coe and Helpman 1995). However, recent studies such as Funk (2001) suggest that exports could be the primary channel of spillovers. From an empirical viewpoint, it is difficult to distinguish between the effects of imports and exports given the high collinearity between the two series. Therefore, in this study, we use the ratio of total trade over GDP as the main variable to measure trade openness.

Foreign Direct Investment Inflows and Outflows (FDII and FDIO)
It has been widely argued that vertical and horizontal linkages resulting from inward FDI facilitate technology spillovers for the host economy. Vertical linkages are formal contacts between multinational enterprises (MNEs) i.e., the FDI source firms and their local suppliers or buyers. The existence of a formal relationship provides an incentive to the MNEs for directly transferring their technology and know-how to the local firms. Spillovers resulting from horizontal linkages, on the other hand, are unintended ‘leaks’. These occur when the competing domestic firms appropriate the MNEs technology through means such as imitation and reverse engineering (OECD 2002). Technology spillovers may also accrue to the host economy when the MNE trained labour relocates to the domestic firms (Fosfuri et al., 2001).

Some of the more recent studies suggest that MNEs undertake FDI with the intention to source technology from the leading firms in the host economy. Based on this theory, it is argued that FDI flows lead to technological externalities in the source economies. Such a view has considerable supporting evidence at the firm level (Driffield and Love 2003). Notwithstanding, the theory does not seem to be supported by the empirical evidence at the macro level (e.g. Kogut and Chang 1991; Anand and Kogut 1997). A possible, but unproven, explanation is that capital outflows lead to hollowing out of domestic industrial base and depletion of the capital market.

Human Capital (HC) and Domestic R&D (DRD)
The endogenous growth literature assigns a central role to human capital and domestic R&D in total factor productivity growth (Lucas 1988; Romer 1990). In that, the inclusion of these variables is imperative to ensure that the role of foreign R&D in technological catching-up is not over stated. Also, the definitions of human capital and domestic R&D share some commonality with absorptive capacity, i.e., the ability to identify, assimilate and exploit foreign technology. As a result, several empirical studies have used human capital and domestic R&D measures as proxies for absorptive capacity (e.g. Iyer et al.,

<table>
<thead>
<tr>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDII</td>
<td>FDIO</td>
<td>TOP</td>
<td>DRD</td>
<td>HC</td>
</tr>
<tr>
<td>G1</td>
<td>G1</td>
<td>G1</td>
<td>G1</td>
<td>G2</td>
</tr>
<tr>
<td>0.019</td>
<td>0.002</td>
<td>0.641</td>
<td>0.012</td>
<td>0.083</td>
</tr>
<tr>
<td>0.011</td>
<td>1.30E-05</td>
<td>0.546</td>
<td>0.006</td>
<td>0.070</td>
</tr>
<tr>
<td>0.305</td>
<td>0.053</td>
<td>2.965</td>
<td>0.143</td>
<td>0.447</td>
</tr>
<tr>
<td>-0.109</td>
<td>-0.023</td>
<td>0.091</td>
<td>0.000</td>
<td>0.004</td>
</tr>
<tr>
<td>0.032</td>
<td>0.005</td>
<td>0.373</td>
<td>0.016</td>
<td>0.076</td>
</tr>
</tbody>
</table>
Iyer, K. *Technology gap, catching up and outward orientation: Analysis of 63 countries* 2008. The proportion of adult population with secondary education is used as a proxy of human capital. Secondary school attainment is the major variable in the literature for gauging the level of human capital (Miles 2004). On the other hand, domestic R&D is measured as the number of scientific and technical journal article publications (per million people).

### 3. Results and Discussion

#### 3.1 Metafrontier ratio (MFR) Estimates

As indicated earlier, we sort the countries in two groups, G1 and G2, and allow for three alternative time-varying specifications of the parameters of the frontier functions and two functional forms. We use dummy variables for intercept and slope changes. The computed log-likelihood values for all the models as well as a series of likelihood ratio tests are reported in Table 1. It is found that all restricted forms of the frontier model are rejected, and thus the translog functional form with time varying intercepts (annually) and slope varying parameters (every five years) is chosen.\(^{12}\)

While MFRs for individual countries are estimated and will be used in the next section, for brevity, we present some graphical results of the MFR growth rates for the two group averages (see Figure 1), as well as the growth rates of MFRs across a subset of countries in each group (see Figure 2). Recall that MFR measures how far a country (and its peer group) is from the world’s technology frontier (metafrontier). Therefore, a positive growth rate in MFR indicates that the technological frontier of the group in question is shifting upwards at a rate faster than that of the metafrontier. In that case the group can be said to be catching-up. On the contrary, a negative growth rate in MFR may be due to the fact that the metafrontier is advancing farther in relative terms, and not necessarily that the group in question is technologically regressing in absolute terms.

Figure 1 plots the yearly average across the 38 countries in G1 (lower-middle income) and 25 countries in G2 (high income). The graph seems to indicate that on average G1, the less developed countries’ group, is managing to keep pace with the metafrontier. In Figure 2, five countries from each group are plotted individually. The upper graph of Figure 2 plots the growth rates of India, China, Brazil and Botswana and Ghana from the lower-middle income group (G1). The lower graph of Figure 2 plots the growth rates for Great Britain, Germany, Singapore, Japan and the USA from the high income group (G2). The countries in the G1 group mostly show negative or stable growth rates in MFR over the sample period except for Botswana, which has had several periods of positive growth rates, indicating some catching up. A large decrease in the growth rate occurs in 1992 for three of the countries, India, China and Brazil. Countries in G2 show a tendency to keep up with the metafrontier, i.e. growth rates are around zero. Singapore is the exception, as it shows some volatility during and after the Asian financial crisis. In both the Japanese and Singaporean cases, there are some large spikes in the growth rate during the sample. It is important to remember that this could have resulted by the metafrontier shifting outwards and these countries simply staying at the same input/output mix point.

\(^{12}\) In all cases a half-normal distribution was used for the efficiency effects and they are significant at the 1 per cent level.
Table 1. Model Specification for Group Stochastic Frontiers

<table>
<thead>
<tr>
<th>SFA Models</th>
<th>Computed Log-Likelihood Group 1</th>
<th>Computed Log-Likelihood Group 2</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cobb-Douglas – Intercept time dummies</td>
<td>11.77062</td>
<td>258.19489</td>
<td></td>
</tr>
<tr>
<td>Translog – Intercept time dummies (M1)</td>
<td>25.21757</td>
<td>398.9179</td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio Test, ( H_0: ) CD, ( H_1: ) Translog</td>
<td>26.89389</td>
<td>281.44606</td>
<td>Reject Cobb-Douglas in both cases</td>
</tr>
<tr>
<td>----------------------------------------------------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
</tr>
<tr>
<td>Cobb-Douglas – Intercept time dummies, slope dummies =1 for ( t&gt;1991 )</td>
<td>14.69665</td>
<td>262.6329</td>
<td></td>
</tr>
<tr>
<td>Translog – Intercept time dummies, slope dummies =1 for ( t&gt;1991 ) (M2)</td>
<td>48.37283</td>
<td>414.4372</td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio Test, ( H_0: ) CD, ( H_1: ) Translog</td>
<td>67.35236</td>
<td>303.6086</td>
<td>Reject Cobb-Douglas in both cases</td>
</tr>
<tr>
<td>----------------------------------------------------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
</tr>
<tr>
<td>Cobb-Douglas – Intercept time dummies, slope changing 5 yearly</td>
<td>15.23707</td>
<td>263.8548</td>
<td></td>
</tr>
<tr>
<td>Translog – Intercept time dummies, slope changing 5 yearly (M3)</td>
<td>51.60447</td>
<td>422.1157</td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio Test, ( H_0: ) CD, ( H_1: ) Translog</td>
<td>72.73479</td>
<td>316.5219</td>
<td>Reject Cobb-Douglas in both cases</td>
</tr>
<tr>
<td>----------------------------------------------------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
<td>---------------------------------</td>
</tr>
<tr>
<td>Likelihood Ratio Test, ( H_0: ) M1, ( H_1: ) M2</td>
<td>46.31054</td>
<td>31.03862</td>
<td>Reject M1</td>
</tr>
<tr>
<td>Likelihood Ratio Test, ( H_0: ) M2, ( H_1: ) M3</td>
<td>6.463272</td>
<td>15.35698</td>
<td>Reject M2</td>
</tr>
</tbody>
</table>

It is not possible to attribute the differences between G1 and G2 to the lack of channels for importing foreign technology. The trade openness and FDI openness ratio of the two groups is fairly comparable on average. Table 2 shows a disaggregated set of statistics for G1 and G2, where G1 has been sub-divided in three groups, Lower Income (LI), Lower-Middle Income (LMI), and Upper-Middle Income (UMI) countries. What the G1 countries are lacking is investment in developing indigenous technology and human capital, which constitute the capacity to absorb foreign technology. For instance, there are on average just about 0.01 research and technical publication outputs per million persons in the G1 group, as compared to 0.90 publications in the G2 group. Likewise, the share of the population with secondary education in the G1 countries on average is around 8 per cent, as compared to roughly 19 per cent in the G2 group.

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Figure 1. Average MFR Growth Rate for Groups 1 and 2

Figure 2. Technological Catching Up across the two groups of countries
Table 2: Mean Values by Income Level

<table>
<thead>
<tr>
<th>Income Level</th>
<th>Group</th>
<th>Human Capital (%)</th>
<th>Domestic R&amp;D (%)</th>
<th>FDII/GDP (%)</th>
<th>FDIO/GDP (%)</th>
<th>TOP/GDP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Income</td>
<td>1</td>
<td>3.16</td>
<td>0.005</td>
<td>2.01</td>
<td>0.03</td>
<td>72.91</td>
</tr>
<tr>
<td>Lower-Middle Income</td>
<td>1</td>
<td>7.84</td>
<td>0.006</td>
<td>1.74</td>
<td>0.15</td>
<td>60.33</td>
</tr>
<tr>
<td>Upper-Middle Income</td>
<td>1</td>
<td>11.39</td>
<td>0.021</td>
<td>1.92</td>
<td>0.22</td>
<td>62.18</td>
</tr>
<tr>
<td>High Income</td>
<td>2</td>
<td>18.72</td>
<td>0.896</td>
<td>2.32</td>
<td>2.11</td>
<td>76.51</td>
</tr>
<tr>
<td>All Groups</td>
<td></td>
<td>12.45</td>
<td>0.363</td>
<td>2.06</td>
<td>0.93</td>
<td>69.05</td>
</tr>
</tbody>
</table>

The next section explores whether any of the variables commonly associated with measuring outward orientation of economies shows any explanatory power of MFR or its growth rate.

3.2. Preliminary Panel Analysis

The main objective of the panel analysis reported bellow is to identify potential determinants of the technology gap and the catching-up process, as suggested in models (2) and (3). Both models are estimated by GMM¹⁴. Table 3 summarizes the results.

The model of MFR levels has a higher explanatory power (R²=0.39). The model displays a robust autoregressive component. The coefficient values of the lag terms of \( \ln\left[\frac{MFR}{(1-MFR)}\right] \) indicate that the effect of an exogenous shock to technology gap will wane out in about two years. Despite this, we observed from the data that MFR levels are not volatile, suggesting that shocks to technology gap are not frequent. As a result, the growth rate of MFR is by and large centring on zero and there is no much variation in the growth rate of MFR to be explained.

Therefore, it is not surprising to see that the explanatory power of model (3) is very poor. Moreover, the growth rate of MFR has a first degree autoregressive component, reflecting the fact that the autoregressive component of the MFR level is of second degree. Model (3) also includes the lagged value of MFR as an explanatory variable. It is found that lagged MFR has a highly significant but negative effect on the MFR growth rate. The results implies that, other things equal, a country further away from the metafrontier will see its gap closing faster. In other words, there is evidence that technologically backward countries catch-up faster than the advanced ones when other conditions are identical.

Besides the lagged values of the dependent variables, the two models also include a number of variables pertaining to outward orientation. Our findings are that both MFR level and MFR growth rate are positively related to foreign direct investment inflows. Trade openness is also positive and significant in the MFR level equation, although not in the growth of MFR equation.

¹⁴ Arellano and Bover (1995).
Foreign direct investment outflows are a significant determinant of MFR level but not its growth. The negative sign of the variable suggests that, if there is any technology sourcing effect associated with FDI outflows, it is outweighed by the hollowing out effect. Domestic R&D is significant in both equations, but with a negative effect. We suspect that this counterintuitive result is related to the fact that science publication may not sufficiently capture all the essence of indigenous R&D, especially those carried out in
industrial rather than in academic institutions. Human capital is significant in both equations; however we observe that the sign of the human capital variable is positive in the MFR growth equation and negative in the level one. The positive sign of the human capital variable in the MFR growth equation is consistent with the hypothesis that accumulation of human capital helps in speeding up the process of technological catching-up.15

The marginal elasticities, at sample median values, from the model in levels are presented in Table 4. A 1% increase in the ratio of trade to GDP is estimated to increase MFR by 0.015% for developed countries and 0.018% for developing countries, and a 1% increase in FDI inflows as a proportion of GDP results in 0.0003% and 0.0004% increase MFR for the developed and developing countries, respectively. Recalling that MFR provides a measurement of potential output, at full efficiency, compared to that of the metatechnology, therefore, the computed elasticity values provide a measurement of potential increase in the productivity of the domestic economy resulting from increased inflow of FDI and increased trade openness of the domestic economy.

### Table 4. Marginal Elasticity from Model in Levels

<table>
<thead>
<tr>
<th></th>
<th>Computed at median of G2</th>
<th>Computed at median of G1</th>
</tr>
</thead>
<tbody>
<tr>
<td>HC</td>
<td>-0.0544</td>
<td>-0.0353</td>
</tr>
<tr>
<td>R_D</td>
<td>-0.1972</td>
<td>-0.0029</td>
</tr>
<tr>
<td>TOP</td>
<td>0.0148</td>
<td>0.0176</td>
</tr>
<tr>
<td>FDII</td>
<td>0.0003</td>
<td>0.0004</td>
</tr>
<tr>
<td>FDIO</td>
<td>-0.0019</td>
<td>-3.17E-06</td>
</tr>
</tbody>
</table>

In summary, the empirical results suggest that there is a tendency for technologically more backward countries to catch-up faster, and FDI inflows, trade openness and the presence of sufficient human capital can speed up this catching-up process.

4. Conclusion

Empirical studies on technological catching-up have been restricted by two constraints. One is related to measuring technological catching-up free from the efficiency component, the other is related to data availability. In this paper, we adopt the newly

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15 When human capital is measured as the proportion of adult population with post secondary education, (rather than secondary education) the human capital variable is significant and positive in both the level and growth equations of MFR. Results of these are available from the authors on request (See, Referee Appendix). Also it has been observed that while there is a rather strong theoretical support for a key role of human capital on growth, the empirical evidence is not clear-cut (Loening 2004).
developed metafrontier technique to obtain an annual measure of technology gap and the rate of technological catching-up (i.e., the growth rate of the estimated metafrontier ratio) which requires data on output, labour and capital only.

Anecdotal evidence from several countries such as Korea and China suggests that the poorer countries can leap to the front by soliciting foreign technologies, investing in domestic innovation abilities and expanding the domestic capacity to absorb the new technologies effectively. This anecdotal evidence is tested within a formal regression model framework. A panel dataset of 63 countries over the period of 1984 to 2000 was applied. Specifically, both the MFR and the annual growth rate of MFR were modelled on a host of explanatory variables representing channels for importing foreign technology (trade openness and foreign direct investment), domestic absorptive capacity (human capital and domestic R&D), the lag of MFR level, and the lag of MFR growth rate in the model where the MFR growth rate is the dependent variable.

A variety of model specifications were examined in a panel setting. It is found that technologically more backward countries can catch-up faster. It is also found that FDI inflows, trade openness and human capital have positive effects on closing the technology gap and speeding up the catching-up process. The size of the elasticities of these factors is computed to provide an indication of the potential increase in productivity resulting from an increase in these factors.

References


Appendix 1: List of sample countries grouped by Income

<table>
<thead>
<tr>
<th>Middle and Lower Income G1</th>
<th>High Income G2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina, Bolivia, Gambia, Botswana, China, Ghana, Brazil, Dominican Republic, India, Chile, Ecuador, Kenya, Colombia, Egypt, Lesotho, Costa Rica, El Salvador, Mali, South Korea, Guatemala, Pakistan, Malaysia, Honduras, Senegal, Mauritius, Indonesia, Togo, Mexico, Jamaica, Panama, Philippines, Peru, Sri Lanka, Thailand, Tunisia, Turkey, Uruguay, Venezuela</td>
<td></td>
</tr>
<tr>
<td>Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States</td>
<td></td>
</tr>
</tbody>
</table>

Appendix 2: Variables, Data Sources and Remarks

<table>
<thead>
<tr>
<th>Variables</th>
<th>Data Source</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (Real GDP)</td>
<td>Penn World Tables - version 6.1 (PWT) (2002)</td>
<td>PWT reports the 1996 real GDP per capita chain measure (RGDPCH). The RGDPCH is a chain index of real per capita GDP of countries measured in 1996 international dollars. The series is constructed after adjusting for price differences across countries and over time. RGDPCH times the population of the country yields the output.</td>
</tr>
<tr>
<td>Capital Stock</td>
<td>Constructed from PWT using the Perpetual Inventory Method</td>
<td>Capital Stock ($K_t$) is constructed as: $K_t=K_{t-1}(1-\theta)+I_t$ where $I$ is investment and $\theta$ the assumed rate of depreciation. $\theta$ is assumed as 6 percent (see, Hall and Jones (1999)). Initial capital stocks are constructed by the assumption that capital and output grow at the same rate. Specifically for countries with investment data beginning in 1950 we set the initial capital stock $K_{1949}=I_{1950}/(g+\theta)$ where $g$ is the 10 year growth rate of output (e.g., from 1950 to 1960). In order to arrive at the capital stock net of residential capital stock, the ratio of residential capital as a fraction of non-residential capital is used. This ratio is computed from PWT version 5.6 for the years until 1992. For all subsequent years, the average ratio over the 1987 to 1992 period is used.</td>
</tr>
<tr>
<td>Total Labour Force</td>
<td>World Development Indicators (2003) (WDI)</td>
<td>Total Labour force comprises people who meet the International Labour Organization definition of the economically active population, i.e., all people who supply labour for the production of goods and services during a specified period.</td>
</tr>
<tr>
<td>Trade Openness (TOP)</td>
<td>WDI</td>
<td>TOP is defined as the ratio of total trade (i.e., exports and imports) to GDP.</td>
</tr>
</tbody>
</table>
Foreign Direct Investment (FDI) inflows and outflows

International Financial Statistics (IFS)

FDI is defined as the net inflows of investment to acquire a lasting management interest (10 per cent or more of voting stock) in an enterprise operating in an economy other than that of the investor. As is usual in the literature, FDI inflows and outflows are measured as a proportion of GDP.

Human Capital

Barro and Lee (2000)

Proportion of Adult Population with Secondary School Attainment

Domestic R&D (DRD)

WDI

Number of Scientific and Technical Journal Articles per million population

Appendix 3: Model of \( \ln\left( \frac{MFR}{I-MFR} \right) \) and \( \bar{MFR} \)

(Human Capital measured as proportion of adult population with post secondary education)

<table>
<thead>
<tr>
<th>Variable \ Dependent Variable</th>
<th>( \ln\left( \frac{MFR}{I-MFR} \right) )</th>
<th>( \bar{MFR} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG(MFR_{t-1} - 1 - \text{LMFR}_{t-1})</td>
<td>0.580594* (6.11E-05)</td>
<td>-0.067527** (0.001031)</td>
</tr>
<tr>
<td>LOG(MFR_{t-2} - 1 - \text{LMFR}_{t-2})</td>
<td>-0.214733** (7.52E-05)</td>
<td></td>
</tr>
<tr>
<td>( \bar{MFR}_{t-1} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FDII_{t-1}</td>
<td>0.114233** (0.033241)</td>
<td>0.024478** (0.006010)</td>
</tr>
<tr>
<td>H</td>
<td>5.407916** (0.037249)</td>
<td>0.121465** (0.017165)</td>
</tr>
<tr>
<td>DRD</td>
<td>-1.207337** (0.001166)</td>
<td>-0.038392** (0.001891)</td>
</tr>
<tr>
<td>FDIO_{t-1}</td>
<td>-0.519010** (0.025826)</td>
<td>-0.010581 (0.013165)</td>
</tr>
<tr>
<td>TOP_{t-1}</td>
<td>0.044744** (0.003864)</td>
<td>0.000726 (0.001034)</td>
</tr>
<tr>
<td>TREND</td>
<td>-0.012327** (0.000175)</td>
<td>-0.000169** (3.63E-05)</td>
</tr>
<tr>
<td>MFR_{t-1}</td>
<td></td>
<td>-0.122720** (0.001733)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.388612</td>
<td>0.061984</td>
</tr>
</tbody>
</table>

* GMM estimates with cross-sectional effects (orthogonal deviations), weighting matrix based on white period, standard errors in brackets, * and ** denote significance at 5 per cent and 1 per cent, respectively.