IMF Staff Papers
Vol. 47, No. 1

International Trade and Productivity Growth: Exploring the Sectoral Effects for Developing Countries

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The paper estimates an empirical relation based on Krugman's "technological gap" model to explore the influence of the pattern of international trade and production on the overall productivity growth of a developing country. A key result is that increased import competition in medium-growth (but not in low- or high-growth) manufacturing sectors enhances overall productivity growth. The authors also find that a production-share weighted average of (technological leaders') sectoral productivity growth rates has a significant effect on the rate of aggregate productivity growth. [JEL F10, F43, O10, O40]

Developing countries do not in general perform research and development (R&D), and they rely largely on technological knowledge produced in industrial countries. Their productivity growth thus depends, to a large extent, on the rate at which they can acquire technology developed by industrial countries. A popular view is that international trade represents an important conduit for the transfer of technology and trade liberalization would thus enable developing countries to achieve faster productivity growth. A number of recent studies have found a positive link between international trade and productivity

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growth in developing countries.[1] Coe, Helpman, and Hoffmaister (1997), for example, provide evidence that increased trade with industrial countries boosts productivity growth of developing countries via R&D spillovers.[2]

Although the role of international trade in facilitating technology transfer is generally recognized, some reservations remain about the view that free trade enhances productivity growth. An important reservation is that the comparative advantage of developing countries is likely to lie in traditional sectors with slow growth. Unrestricted trade could trap their production in such sectors and, in fact, lead to a lower rate of productivity growth.[3] There is little empirical evidence that bears directly on the role that a developing country's pattern of international trade and production can play in determining its overall productivity growth. Exploring this link is the main objective of this paper. For this purpose, the paper examines the determinants of productivity growth in developing countries, using a methodology that incorporates the influence of the sectoral composition of production, as well as the influence of openness at the sectoral level.

Our empirical analysis uses a multisector framework based on Krugman's (1985) model of technology gap. In this model, the best-practice technology improves at constant but different rates across sectors. Less-advanced countries face longer time lags in acquiring best-practice techniques. They are thus farther behind the technological frontier (have larger technology gaps) and have a comparative disadvantage in sectors where productivity grows more rapidly. The view that international trade facilitates the transfer of technology is incorporated in the model by allowing a country's technology lag in a sector to be inversely related to the openness of the sector. The aggregate rate of productivity growth in the long run is a weighted average of sectoral growth rates with weights given by production shares. In this setup, although increased openness of a sector does not have a permanent effect on the productivity growth rate, it can raise the growth rate in transition to the long run by shortening the technology lag for the sector.

The above framework is implemented using a panel data set that includes 33 developing countries and covers more than two decades. Data for large industrial countries (that are likely to be technological leaders) are used to estimate long-run rates of sectoral productivity growth. Sectoral indexes of openness are based on exports and imports normalized by domestic production. The multisector framework enables us to investigate whether the effect of openness on productivity growth differs between sectors with different growth rates.

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[1]There is also a considerable literature linking growth of GDP or per capita GDP with various aggregate measures of openness. See Edwards (1993) for a review of the early literature. Rodríguez and Rodrik (1999) provide a critical evaluation of the recent empirical literature linking openness and economic growth.

[2]Jaumotte (1998) finds evidence that more trade with industrial countries enables developing countries to narrow their technological gap at a faster rate. Moreover, Hakura and Jaumotte (1999) find that the greater the share of sectors with large intra-industry trade, the faster these countries catch up.

[3]Such a possibility is discussed in the endogenous-growth literature. See Lucas (1988, section 5) for an example based on a model with learning by doing. Grossman and Helpman (1991, chaps. 18–19) discuss a number of cases where free trade reduces productivity growth of a technologically disadvantaged country. Also see Matsuyama (1996) for a demonstration that international trade can lead to income disparities between otherwise symmetrical countries via agglomeration effects.

I. Basic Framework

This section describes a multisector framework based on Krugman's (1985) model of technology gap, which underlies the paper's empirical analysis. Let $A_j^*(t)$ denote total factor productivity (TFP) corresponding to the best-practice technology for sector j at time t. Assume that it grows at a constant rate and can thus be expressed (after dropping the time argument) as

$$A_j^* = \exp[\gamma_j t]. \tag{1}$$

The rate, γ_j, orders sectors according to a technology scale (for example, high-tech sectors have relatively large growth rates). Countries acquire the best-practice technology with a time lag. Thus, country i's TFP in sector j evolves according to

$$A_j^i = \exp[\gamma_j(t - \lambda_j^i)], \tag{2}$$

where λ_j^i is the country's sectoral technology lag. This lag equals zero for the technological leader in the sector that has immediate access to the best-practice technology.

According to equations (1) and (2), a country's sectoral productivity gap (relative to the technological leader) is $A_j^*/A_j^i = \exp[\gamma_j \lambda_j^i]$. This gap depends on both the growth rate and the technology lag for the sector. Note that if a country has the same technology lag in all sectors ($\lambda_j^i = \lambda^i$), the higher a sector's growth rate is, then the larger will be the productivity gap in that sector. Developing countries would face longer technology lags than industrial countries. They would thus be farther away from the technology frontier in high-growth sectors and tend to have a comparative disadvantage in these sectors.

Let $g_j^i (\equiv \dot{A}_j^i/A_j^i)$ denote the rate of country i's TFP growth in sector j (with a dot over a variable representing its derivative with respect to time), and use equation (2) to obtain

$$g_j^i = \gamma_j(1 - \dot{\lambda}_j^i). \tag{3}$$

In the long run, the technology lag would be constant and country i's TFP growth rate in each sector would equal the rate for the technological leader. In transition to the long run, however, the technology lag could decrease or increase and thus the country's sectoral TFP could grow faster or slower than the leader's TFP.

The technology lag can depend on a number of factors. This paper focuses on the hypothesis that openness facilitates the transfer of technology. The relation between the technology lag and openness is expressed as

$$\lambda_j^i = \phi_j(v_j^i), \tag{4}$$

where v_j^i is an index of openness for country i's sector j and $\phi_j'(v_j^i) < 0$.[4] The function $\phi_j(v_j^i)$ is assumed, for simplicity, to be the same for all countries but is allowed to differ across sectors to let the effect of openness in a sector depend on the technology rating of the sector. The technology gap model assumes that a sector's position on the technology scale is related to its rate of growth. Sectors with low growth rates, for example, are considered to have relatively simple technology. In these sectors, the technology gap between more and less advanced countries would be already small and there would be little scope for openness to reduce the gap further. The effect of openness on the technology lag $[\phi_j'(v_j^i)]$ is thus likely to be small in the case of low-growth sectors. As the growth rate of a sector increases, two opposing forces may be at work in determining the effect of openness. On the one hand, sectors with higher growth rates may provide a greater potential for the transfer of technology via international trade. It may be more difficult, on the other hand, for less advanced countries to absorb the more complex technology of rapidly advancing sectors. As it is not clear how the effect of openness depends on the growth rate of a sector at the upper end of the technology scale, this paper's empirical analysis lets the data determine this relation. A number of plausible variations of equation (4) are also explored in the empirical analysis.

The choice of the openness index depends on how international trade affects the technology transfer process. There are several mechanisms through which an increase in international trade could facilitate the transfer of technology. First, increased contact with foreign agents could lead to a more rapid transmission of foreign technological knowledge. Second, greater exposure to foreign products may make imitation easier. Both of these mechanisms suggest that transfer of technology in a sector would depend largely on trade within the sector. It is also possible that trade in one sector may enhance productivity in another via input-output relations. For example, larger imports of foreign intermediates could increase the access to foreign technological improvements embodied in such goods and facilitate production of final goods. The relative importance of exports and imports in technology transfer would depend on the mechanism at work. For example, imports are crucial in acquiring embodied foreign technology and would play a more important role in imitation. Exports, on the other hand, could provide greater contact with foreign agents than imports. The paper's empirical analysis assumes that the openness index depends on both import and export intensities and lets the relative importance of each intensity be determined by the data.

The implications of the above model can also be derived for the aggregate rate of TFP growth. Letting $\bar{g}^i$ denote this rate, we can define it as the following weighted average of the sectoral rates:

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[4]The above formulation relates the technology lag to openness in levels to ensure (as assumed in the model) the existence of stable sectoral technology gaps in long-run equilibrium. If, for example, it is assumed instead that the change or the rate of change in the technology lag is inversely related to the level of openness in a sector, then a given level of openness in a sector would cause the sectoral technology gap to keep on decreasing until it disappears.

$$\bar{g}^i = \sum_j s_j^i g_j^i, \tag{5}$$

where s_j^i is the output share of sector j in country i. Using equations (3)–(5), we obtain the following key relation that underlies the empirical analysis in the next section:

$$\bar{g}^i = \sum_j s_j^i \gamma_j - \sum_j s_j^i \gamma_j \phi_j'(v_j^i)\dot{v}_j^i. \tag{6}$$

In equation (6), the first term on the right-hand side represents the aggregate growth rate in the long run. Note that if output shares vary across countries, the aggregate rate will not converge among countries in the long run. In this case, the long-run aggregate growth would be slower for countries that specialize in the products of low-growth sectors. The second term captures transitional dynamics caused by changes in technology lags arising from sectors becoming more or less open. The effect of a change in a sector's openness index $(\dot{v}_j^i)$ can vary from one sector to another because of differences not only in s_j^i and γ_j but also in $\phi_j'(v_j^i)$. Note that if $\phi_j'(v_j^i)$ tends to be small for sectors with low γ_j, increased openness of such sectors would have little impact on overall productivity growth.

The above model could be relevant for a country at any stage of economic development, but it is designed especially for developing countries where international trade is a major source of technology transfer. As the TFP data are available for most developing countries only at the aggregate level, the empirical analysis below focuses on relation (6), which links overall productivity growth to sectoral composition of production and international trade, and estimates a regression equation based on this relation.

II. Data

This section briefly describes some key features of the data used in the empirical analysis. Sources of all data and further details are given in Data Appendix. To estimate the empirical model based on relation (6), the paper uses a data set that includes 44 countries (of which 33 are developing countries) and the 1970–93 period.[5] The data set also covers 10 sectors. As the paper is mainly concerned with the role of international trade in manufacturing industries, manufacturing is broken down into nine sectors (at the 2-digit ISIC level), but all nonmanufacturing industries are aggregated into one sector.[6]

The estimates of long-run sectoral growth rates, γ_j, are based on the 1970–94 TFP growth performance of large OECD countries, France, West Germany, Japan, the United Kingdom, and the United States. This group includes countries with large R&D expenditures, which are likely to be close to the technological frontier

[5]For five of these countries, Argentina, Bangladesh, Dominican Republic, Kenya, and Panama, only a part of the period is covered.

[6]Satisfactory data on sectoral composition of nonmanufacturing is also difficult to obtain for many developing countries in our sample.

(have short technology lags). Simple averages of annual sectoral TFP growth rates over 1970–94 and the five large countries are used to measure γ_j.[7] For each country, the TFP growth rate of a sector is calculated as the difference between the rate of growth of sectoral output (value added) and a Cobb-Douglas weighted average of growth rates of capital and labor in the sector.

For each of the 10 sectors, Table 1 shows the mean (and the standard deviation) of the long-run sectoral TFP growth rates for the five large countries. On the basis of this measure, the table classifies the nine manufacturing sectors into low-, medium-, and high-growth groups. The long-run TFP growth rate for the nonmanufacturing sector is very close to the growth rates for manufacturing industries in the low-growth group. The sectoral means (and standard deviations) of the long-run sectoral TFP growth rates for a sample of 12 OECD countries are also shown in Table 1. These data are broadly consistent with the three-way classification of manufacturing sectors (according to their TFP growth trends) suggested by the large-country data.[8]

Estimates of sectoral shares, s_j^i, are based on value-added data. There are a number of gaps in this data and the missing values are imputed or estimated. The data for factor inputs, especially capital, by sectors are not available for most non-OECD countries, and thus, sectoral growth rates (g_j^i) or the weighted average of these rates ($\bar{g}^i$) cannot be estimated for these countries. Availability of aggregate data, however, makes it possible to estimate the rate of growth of aggregate TFP for all countries in the sample. This rate is calculated as the difference between the rate of growth of aggregate output and a Cobb-Douglas weighted average of growth rates of total capital and labor, and is used as a proxy for $\bar{g}^i$.[9]

[7]Annual growth rates for a large industrial country i's sector j could be expressed as $g_{jt}^i = \gamma_j + \varepsilon_{jt}^i$, where ε_{jt}^i represents deviations from the long-run sectoral growth rates (assumed to be constant over time). The large-country panel data suggest that country effects are absent and γ_j are stable over time in this relation. (In a regression of g_{jt}^i on sectoral dummy variables, F-tests indicate that fixed country effects are not present and the coefficients of sectoral dummy variables are not different between the two halves of the sample). Variability in ε_{jt}^i, however, accounts for much of the variation in g_{jt}^i. We assume that this variability largely reflects the influence of short-run factors and the long-period average of ε_{jt}^i across all large countries tends to be small for each sector. We thus consider our measure a useful proxy for γ_j.

[8]An exception is Basic Metal Industries, which would belong to the high-growth group according to the 12-country sample.

[9]Our measure differs from $\bar{g}^i$ (as defined in equation (5)) essentially in that it uses growth rates of aggregate capital and labor rather than production-share-weighted averages of these factors' sectoral growth rates. Using the (two-factor) Cobb-Douglas production function and letting a hat over a variable denote its growth rate, we have $\bar{g}_j^i = \sum_j s_j^i[\hat{Y}_j^i - \beta_j \hat{K}_j^i - (1-\beta_j)\hat{L}_j^i]$, where Y_j^i, K_j^i and L_j^i represent country i's (value-added) output, capital, and labor in sector j, and β_j is the share of capital in sector j. Our measure equals $\hat{Y}^i - \beta\hat{K}^i - (1-\beta)\hat{L}^i$, where $Y^i = \sum_j Y_j^i$, $K^i = \sum_j K_j^i$, $L^i = \sum_j L_j^i$, and β is capital's aggregate share. Assuming that factor prices are the same in each sector so that $\beta = \sum_j s_j^i \beta_j$ and noting that $\hat{Y}^i = \sum_j s_j^i \hat{Y}_j^i$, we can express the discrepancy between our measure and $\bar{g}^i$ as $\sum_j s_j^i[\beta_j(\hat{K}_j^i - \hat{K}^i) + (1-\beta_j)(\hat{L}_j^i - \hat{L}^i)]$. This expression would tend to be small if deviations between sectoral and aggregate growth of capital and labor are uncorrelated with production shares. The discrepancy would be included in the error term in our regression equations discussed below and is not likely to be systematically related to the regressors in these equations based on long-run growth rates and sectoral changes in openness.

Table 1. Sectoral TFP Growth Rates
(in percent)

ISIC Code	Sector	Average Rates 1970–94 Large countries[a]	ISDB countries[b]
Manufacturing			
Low Growth			
31	Food, Beverages and Tobacco	0.61	1.07
		(0.37)	(0.23)
34	Paper, Paper Products, Printing & Publishing	0.62	0.88
		(0.46)	(0.32)
39	Other Manufacturing Industries	0.59	1.00
		(0.77)	(0.57)
Medium Growth			
33	Wood and Wood Products	1.06	1.22
		(0.48)	(0.43)
36	Non-Metallic Mineral Products, Except Fuel	1.26	1.34
		(0.53)	(0.43)
37	Basic Metal Industries	1.23	2.39
		(0.86)	(0.58)
High Growth			
32	Textile, Wearing Apparel and Leather	1.82	1.91
		(0.46)	(0.29)
35	Chemicals & Chemical Products	1.72	2.98
		(0.63)	(0.40)
38	Fabricated Metal Products, Machinery and Equipment	1.87	1.94
		(0.41)	(0.29)
Nonmanufacturing		0.74	0.79
		(0.17)	(0.10)
Total Industries		1.28	1.39
		(0.17)	(0.10)

Source: See Data Appendix.

Notes: The sectoral TFP growth rates represent simple averages of annual rates from 1970–94 for countries included in the group (excluding any missing observations). The rates for total industries are based on aggregate TFP data. Standard errors are shown in parentheses.

[a]This group comprises France, West Germany, Japan, the United Kingdom, and the United States.

[b]This group includes Belgium, Canada, Denmark, France, Finland, West Germany, Italy, Japan, Norway, Sweden, the United Kingdom, and the United States. Although Australia and the Netherlands are also in the ISDB sample, their data on the TFP index is missing.

Table 2 shows the 1970–93 aggregate TFP growth rate for each country in our sample and averages of these rates for different regions. There is considerable variation in aggregate TFP growth rates across countries and regions. East Asia shows the highest TFP growth rate while sub-Saharan Africa and Latin America register the lowest rates. Table 2 also shows (1970–93) average shares of the three manufacturing groups as well as nonmanufacturing. The fast-growing East Asia has the highest share of high-growth manufacturing sectors and the lowest share of low-growth sectors (nonmanufacturing plus low-growth

Table 2. Aggregate TFP Growth and Sectoral Production Shares
(in percent)

	Average	Average Sectoral Production Shares			
	TFP Growth	Manufacturing			Nonmanufacturing
Country	1970–93	High	Medium	Low	
Algeria	–1.13	4.59	2.39	2.87	90.15
Argentina[a]	0.41	18.03	2.98	7.77	71.23
Australia	0.59	9.18	3.85	4.96	82.02
Austria	0.52	13.84	5.42	5.98	74.76
Bangladesh[a]	0.68	5.96	0.65	2.97	90.41
Cameroon	–1.00	3.42	2.06	6.46	88.08
Canada	0.12	8.97	2.84	5.09	83.10
Chile	1.63	7.13	6.22	6.29	80.36
Colombia	0.99	10.91	2.34	8.29	78.47
Cyprus	2.41	6.37	2.84	5.52	85.27
Denmark	0.71	9.29	2.09	5.83	82.78
Dominican Republic[b]	–0.22	3.69	1.14	13.23	83.31
Ecuador	1.66	9.05	2.33	7.00	81.63
Egypt	0.47	10.38	2.59	4.06	82.98
Finland	0.96	11.11	3.82	8.16	76.91
Germany	0.88	22.39	4.62	5.24	67.75
Ghana	–0.54	3.27	2.46	3.94	90.32
Greece	0.65	9.04	2.88	4.14	83.94
Honduras	0.16	4.02	2.01	7.78	86.19
India	1.01	10.42	2.74	2.49	84.35
Iran	–1.71	5.82	2.44	2.12	89.60
Jamaica	–1.32	7.36	1.51	9.18	81.95
Japan	0.38	19.32	4.77	5.51	70.40
Jordan	0.46	5.20	3.29	4.07	87.44
Kenya[c]	1.54	4.71	0.98	4.73	89.59
Malaysia	1.26	11.01	3.57	5.05	80.38
Malta	3.67	15.69	2.24	7.73	74.35
Mauritius	2.38	9.23	1.10	8.94	80.73
Pakistan	1.46	8.19	1.81	4.53	85.45
Panama[c]	0.35	3.46	1.21	6.76	88.54
Peru	–1.36	11.76	3.75	7.23	77.46
Philippines	–0.53	11.45	2.89	10.79	74.88
South Africa	–1.03	12.13	4.52	5.18	78.17
Senegal	–0.52	4.04	0.87	7.35	88.65
Singapore	1.88	20.75	1.67	3.22	74.36
South Korea	1.90	17.50	3.95	5.86	72.70
Sri Lanka	0.72	8.60	1.81	8.07	81.53
Sweden	0.30	12.69	3.72	5.59	78.00
Turkey	1.20	11.01	3.01	4.23	81.75
United Kingdom	0.67	14.50	3.01	5.49	77.00
Uruguay	1.03	13.40	1.58	9.33	75.69
United States	0.36	13.61	2.30	4.96	79.14
Venezuela	–1.34	10.97	2.51	4.83	81.71
Zimbabwe	–0.23	10.44	3.99	7.47	78.10

Table 2. *(concluded)*

Country	Average TFP Growth 1970–93	Average Sectoral Production Shares: Manufacturing High	Medium	Low	Nonmanufacturing
Regions					
East Asia	1.13	15.18	3.02	6.23	75.58
Industrial countries	0.61	13.09	3.58	5.54	77.80
Latin America	0.18	9.07	2.51	7.97	80.59
Middle East and North Africa	0.69	8.01	2.63	4.39	84.96
South Asia	0.97	8.29	1.75	4.52	85.44
Sub-Saharan Africa	0.09	6.75	2.28	6.29	84.80

Source: See Data Appendix.

Notes: The average sectoral production shares are simple averages of values for five subperiods, 1970–75, 1975–80, 1980–85, 1985–90, and 1990–93. The shares for each manufacturing group represent the sum of the shares for the three sectors in the group. The regional shares are simple averages of shares of countries in the region.

[a]First subperiod data are missing.

[b]Fourth and fifth subperiod data are missing.

[c]Fifth subperiod data are missing.

manufacturing). In contrast, slow-growing sub-Saharan Africa has the lowest share of the high-growth sectors and (along with South Asia) the highest share of the low-growth sectors. The intercountry differences in sectoral shares, however, are small and thus would account for only a limited variation in cross-country productivity growth. For example, if East Asian production shares were used instead of sub-Saharan African shares as weights, the weighted average of long-run sectoral growth rates (i.e., $\sum_j s_j^i \gamma_j$) would increase by only 0.1 percent.[10]

The sectoral openness index is based on x_j^i and m_j^i, which are defined, respectively, as the ratios of exports and imports to value added in country i's sector j. Table 3 shows the average change in the sectoral import and export ratios over the sample period for the nine manufacturing sectors and the three manufacturing groups. As the table indicates, changes in the trade ratios tend to vary considerably across manufacturing groups, and thus the data for total manufacturing is generally not representative of sectoral changes. For example, sub-Saharan Africa registers the highest change in both import and export ratios for all manufacturing, but the disaggregated data reveals that these changes mainly reflect increases in low-growth sectors. A similar pattern holds for import ratios of the Middle East and North Africa region, which has the second highest increase in aggregate import ratios over the period. On the other hand, although East Asia exhibits a relatively small increase in the import ratio

[10]Averages of sectoral production shares and growth rates were used in this calculation.

Table 3. Indicators of Changes in Sectoral Openness

	Average Change							
	All manufacturing		High growth		Medium growth		Low growth	
Country	Import ratio	Export ratio	Import ratio	Export ratio	Import ratio	Export ratio	Import ratio	Export ratio
Algeria	0.037	–0.001	0.041	0.008	0.025	–0.002	0.044	–0.008
Argentina[a]	0.005	0.001	0.017	0.001	–0.016	0.004	0.016	–0.003
Australia	0.024	0.013	0.031	0.008	0.008	0.016	0.032	0.014
Austria	0.032	0.021	0.047	0.034	0.026	0.015	0.023	0.012
Bangladesh	0.024	0.013	0.044	0.027	–0.006	0.002	0.035	0.010
Cameroon	–0.152	–0.080	0.616	0.067	–0.058	–0.054	–1.015	–0.253
Canada	0.032	0.022	0.044	0.027	0.023	0.026	0.029	0.014
Chile	0.099	0.049	0.094	0.010	0.010	0.055	0.193	0.081
Colombia	0.016	0.019	0.020	0.014	0.020	0.004	0.006	0.038
Cyprus	0.053	0.021	0.119	0.033	–0.005	0.005	0.047	0.024
Denmark	0.005	0.021	0.024	0.038	–0.004	0.033	–0.004	–0.007
Dominican Republic[b]	–0.397	0.341	–0.382	0.086	–0.129	0.292	–0.679	0.643
Ecuador	0.005	0.015	0.001	0.005	–0.048	0.008	0.062	0.031
Egypt	0.120	0.005	0.034	0.004	0.094	0.006	0.231	0.006
Finland	–0.001	0.007	0.017	0.019	–0.014	0.001	–0.005	0.000
Germany	0.028	0.017	0.039	0.019	0.021	0.015	0.024	0.016
Ghana	0.218	1.011	0.268	0.003	0.031	0.043	0.355	2.987
Greece	0.060	0.021	0.044	0.021	0.027	0.030	0.108	0.014
Honduras	0.017	–0.020	–0.052	–0.008	0.155	–0.055	–0.053	0.004
India	–0.004	–0.006	0.003	0.015	0.015	0.002	–0.030	–0.035
Iran	–0.088	–0.005	–0.017	–0.002	–0.109	–0.003	–0.139	–0.011
Jamaica	0.073	0.078	0.067	0.170	–0.168	0.001	0.319	0.064
Japan	0.003	0.000	0.006	0.002	0.000	0.000	0.003	–0.003
Jordan	0.769	0.225	0.252	0.068	0.035	0.034	2.021	0.572
Kenya[c]	0.075	0.019	0.025	0.012	0.205	0.031	0.004	0.017
Malaysia	–0.050	0.047	–0.088	0.026	0.014	–0.006	–0.077	0.122
Malta	–0.002	0.050	0.040	0.113	–0.026	0.003	–0.020	0.034
Mauritius	0.056	0.047	0.025	0.068	0.131	0.007	0.013	0.065
Pakistan	–0.002	0.018	0.030	0.023	–0.038	0.002	0.002	0.028
Panama[c]	1.907	0.056	3.462	0.059	0.226	0.095	1.921	0.016
Peru	0.001	–0.001	0.002	0.006	–0.002	–0.009	0.001	0.001
Philippines	0.001	0.007	0.003	0.024	0.000	–0.035	–0.001	0.030
South Africa	–0.005	0.003	–0.007	0.007	–0.002	0.024	–0.007	–0.021
Senegal	1.730	0.737	–0.258	–0.087	–0.125	0.003	5.573	2.295
Singapore	0.341	0.188	0.062	0.177	0.666	0.238	0.294	0.149
South Korea	–0.006	0.010	–0.022	0.027	–0.011	–0.005	0.013	0.007
Sri Lanka	0.092	0.034	0.158	0.053	0.093	0.009	0.023	0.040
Sweden	0.035	0.025	0.071	0.032	0.016	0.028	0.019	0.014
Turkey	0.017	0.015	0.005	0.022	0.011	0.012	0.035	0.013
United Kingdom	0.027	0.018	0.038	0.026	0.019	0.018	0.025	0.009
Uruguay	0.002	0.007	0.027	0.023	–0.040	0.005	0.019	–0.008
United States	0.015	0.009	0.019	0.011	0.011	0.009	0.015	0.007
Venezuela	0.048	0.016	0.067	0.003	0.022	0.028	0.057	0.016
Zimbabwe	0.055	0.029	0.107	0.022	0.032	0.044	0.027	0.020

Table 3. *(concluded)*

Country	All manufacturing Import ratio	All manufacturing Export ratio	High growth Import ratio	High growth Export ratio	Medium growth Import ratio	Medium growth Export ratio	Low growth Import ratio	Low growth Export ratio
	Average Change							
Regions								
East Asia	0.071	0.063	–0.011	0.064	0.168	0.048	0.057	0.077
Industrial countries	0.024	0.016	0.035	0.021	0.012	0.017	0.024	0.008
Latin America[d]	–0.013	0.050	–0.014	0.031	–0.020	0.033	–0.006	0.087
Middle East and North Africa	0.148	0.049	0.078	0.037	0.002	0.007	0.364	0.103
South Asia	0.027	0.015	0.059	0.029	0.016	0.004	0.007	0.011
Sub-Saharan Africa	0.282	0.252	0.111	0.013	0.031	0.014	0.707	0.730

Source: See Data Appendix.

Notes: The import (export) ratio is sectoral imports (exports) divided by sectoral value added. The average change in the import (export) ratio is the simple average of the change over the following subperiods: 1970–75, 1975–80, 1980–85, 1985–90, 1990–93.

[a]First subperiod data are missing.

[b]Fourth and fifth subperiod data are missing.

[c]Fifth subperiod data are missing.

[d]Excludes Panama.

for all manufacturing, it experiences the largest increase in import ratios for the medium growth sectors.

III. Results

The empirical model is specified as

$$\bar{g}_t^i = a_1 \sum_j s_{jt}^i \gamma_j + a_{2j} \sum_{j \neq N} s_{jt}^i \gamma_j \Delta v_{jt}^i + u_t, \qquad (7)$$

where N represents the nonmanufacturing sector, u_t is an error term and a_1 and a_{2j} are parameters of the model. This specification can be derived from relation (6) by assuming that the function $\phi_j(.)$ applies only to manufacturing sectors and using a linear approximation for this function (and measuring time in discrete units so that $\dot{v}_j^i$ is replaced by Δv_{jt}^i). Relation (6) implies that $a_1 = 1$ and $a_{2j} > 0$.

As the theoretical model underlying equation (7) abstracts from short-run (cyclical) effects, a 3–5 year interval is likely to be a more appropriate time unit than a year. The 1970–93 sample period is thus divided into five subperiods, 1970–75, 1975–80, 1980–85, 1985–90 and 1990–93, and a panel based on these subperiods is constructed. For each subperiod, $\bar{g}_t^i$, γ_j, and Δv_{jt}^i are expressed as annual rates and s_{jt}^i as the average value for the subperiod. As discussed in Data Appendix, estimates of the sectoral TFP growth rates, γ_j, are adjusted to make their weighted average conform to estimates of the aggregate TFP growth rate, $\bar{g}^i$, which are obtained from a different source.

Table 4. Basic Regressions

Independent variable	Regression (1)	Regression (2)	Regression (3)	Regression (4)
$\sum_j s^i_{jt}\gamma_j$	1.34**	1.25**	1.16**	1.14**
	(0.40)	(0.41)	(0.42)	(0.43)
$\sum_j s^i_{jt}\gamma_j \Delta m^i_{jt}$		7.79		6.33
		(10.02)		(10.54)
$\sum_j s^i_{jt}\gamma_j \Delta x^i_{jt}$			15.45	11.16
			(11.75)	(13.67)
R^2	0.014	0.014	0.012	0.015
Adjusted R^2	0.014	0.009	0.007	0.006

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations for each regression is 214. Heteroskedasticity-consistent standard errors are shown in parentheses. One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level.

We focus on the case where the openness index for a sector, v^i_{jt}, depends on international trade within the sector. We use the following three measures of this index: (1) the import ratio, m^i_{jt}, (2) the export ratio, x^i_{jt}, and (3) a linear combination of the two ratios (with coefficients of each ratio estimated by the regression). Table 4 shows estimates of equation (7) under the assumptions that a_{2j} is the same for all manufacturing sectors. Regression (1) in the table excludes the effect of the trade variable (i.e., the term including Δv^i_{jt}) while regressions (2)–(4) include this variable using the import, export, and linear-combination measures. In all of these regressions, the effect of the term representing the weighted average of long-run sectoral TFP growth rates is significant. Its coefficient, moreover, is not significantly different from one. This finding is consistent with relation (6). The coefficients of trade variables in regressions (2)–(4) have the predicted positive sign but are not significantly different from zero.[11]

Next, to test whether the effect of a sector's trade variable depends on its rate of growth, Table 5 allows a_{2j} to vary across low-, medium-, and high-growth sectors.[12] The results are sensitive to the index used to measure openness. The effect of the trade variable for the medium-growth sectors is positive and significant in regression (1) based on imports, whereas in regression (2), which is based on exports, it is the trade variable for high-growth sectors that exerts a positive and significant effect. In regression (3), which uses the linear-combination measure, the effect of the export variable (for high-growth sectors) becomes less significant, while that of the import variable remains robust (for

[11] The introduction of trade variables in the regression also makes the coefficient on the weighted-average-growth term closer to the predicted value of one.

[12] We also examined the general case where a_{2j} differs across all nine manufacturing sectors. In this case, however, it is difficult to obtain precise estimates of a_{2j} for each sector because of multicollinearity.

Table 5. Regressions Distinguishing Sectoral Trade Effects

Independent variable	Regression (1)	Regression (2)	Regression (3)
$\sum_{j} s_{jt}^{i}\gamma_j$	1.19** (0.40)	1.21** (0.43)	1.20** (0.42)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	3.76 (70.80)		26.26 (143.53)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	339.42** (79.07)		356.11** (78.28)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	–6.76 (9.33)		–8.00 (9.50)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j \Delta x_{jt}^{i}$		29.37 (78.58)	–66.42 (370.71)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j \Delta x_{jt}^{i}$		–117.16 (79.78)	–150.04* (75.32)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j \Delta x_{jt}^{i}$		25.92* (12.44)	16.91 (11.64)
R^2	0.077	0.031	0.105
Adjusted R^2	0.064	0.017	0.079

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations for each regression is 214. Heteroskedasticity-consistent standard errors are shown in parentheses. l, m, and h denote low-, medium-, and high-growth sectors. One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level.

medium-growth sectors).[13] These results suggest that imports represent a more important vehicle for technology transfer and import-induced transfers occur mainly in medium-growth sectors. Table 5 also shows that regardless of the openness index used, the effect of trade variables is insignificant for low-growth sectors. Thus, opening of traditional sectors to international trade appears to have little impact on productivity growth.

Coefficient estimates for the trade variables of the medium-growth sectors are very large compared with other sector's trade variables. This result could represent the influence of large outliers and this possibility is examined below. Note, however, that these estimates do not imply an implausibly large effect of a change

[13]The coefficient of the export variable for medium-growth sectors is negative and significant in this regression, which is inconsistent with the theory. A problem with including both import and export variables in the same regression, however, is that import- and export-based indexes of changes in sectoral openness are likely to be inversely correlated with each other. Thus, an increase in the import index, for example, would be reflected not only in an increase in its measure, Δm_{jt}^{i}, but also in a decrease in the measure of the export index, Δx_{jt}^{i} (via the negative correlation between the two indexes). Such an effect could account for the results of regression 3 in Table 5. The above problem is avoided in the empirical analysis below, which focuses on regressions based on only import variables.

in the medium-growth import ratio on aggregate productivity growth. Using the average sub-Saharan African production shares and adjusted estimates of γ_j for medium-growth sectors, for example, estimates of a_{2j} for this group in Table 5 imply that an increase in the import ratio (for each sector in the group) by 0.1 would raise aggregate productivity growth only by approximately 0.6 percent. This effect would not change much if shares for other developing regions were used instead of sub-Saharan African shares.[14]

Our sample includes OECD countries, and the growth effects of openness may be less important and different for these countries. To examine this possibility, Table 6 repeats regressions in Table 5 but lets a_{2j} differ between OECD and developing countries for each growth group. For developing countries, the trade variable continues to have a strong effect for medium-growth sectors in the regressions using the import (or the linear-combination) measure and for high-growth sectors in the export-based regression. Thus, the results for developing countries are similar to those for the whole sample. For OECD countries, however, the effect of trade variables is not significantly different from zero for any growth group in all regressions. This effect, however, is not precisely estimated and, in fact, the hypothesis that the trade effect is the same for both developing and OECD countries cannot be rejected.

We undertake a number of tests to examine the robustness of the key finding that the medium-growth import ratio exerts a significant effect on productivity growth. One possibility is that this result is driven by the experience of a particular region such as East Asia where imports of medium growth sectors increased sharply (see Table 3). To investigate this possibility, regression (1) in Table 5 was reestimated excluding East Asian countries, but this exclusion did not affect the results much.[15] Regression (1) in Table 5 was also reestimated, excluding a number of observations with unusually large values of change in the import ratio. Even after dropping these outliers, the effect of the medium-growth variable remained strong.[16]

Estimation in the paper has focused on specifications implied by our technology-transfer model, which may have left out a number of possible determinants of productivity growth. To control for omitted determinants that are specific to countries and subperiods, regressions (1)–(3) in Table 7 introduce fixed country and time effects, separately as well as jointly, into the regression based on import variables. *F* tests in these regressions do not reject the hypothesis that both types

[14]The effect on sector j's productivity growth rate equals $a_{2j}\gamma_j \Delta m^i_{jt}$ and would be clearly much larger than the effect on aggregate productivity growth. Note, however, that the estimates of a_{2j} in Table 5 are based on the assumption that an increase in m^i_{jt} reduces the technology lag only in sector j. If technological benefits also spill over to other sectors (a possibility discussed below), a_{2j} estimates may overstate the within-sector effect.

[15]In this regression, the coefficient of the medium-growth import variable equals 326.0 (with a standard error of 104.5). Moreover, neither this coefficient nor its significance is affected much by the exclusion of each of the other five regions, one at a time.

[16]Plots of the data on Δm^i_{jt} suggest 11 large outliers with $|\Delta m^i_{jt}| > 5$. In the regression excluding these observations, the coefficient of the medium-growth import variable is reduced slightly to 288.0 (with a standard error equal to 89.9), but it remains significant.

Table 6. Regressions Distinguishing OECD and Developing Countries

Independent variable	Regression (1)	Regression (2)	Regression (3)
$\sum_{j} s_{jt}^{i}\gamma_j$	1.27** (0.46)	1.28** (0.47)	1.27** (0.50)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_l$	3.02 (71.50)		16.77 (147.09)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_O$	–97.40 (1049.41)		210.36 (1059.62)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_l$	347.54** (81.08)		361.29** (80.84)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_O$	83.01 (209.69)		199.84 (227.88)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_l$	–6.87 (9.45)		–8.13 (9.61)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j\Delta m_{jt}^{i}D_O$	–10.50 (28.62)		–2.39 (25.45)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_l$		30.56 (75.26)	–39.56 (382.13)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_O$		–131.73 (775.73)	–451.61 (862.81)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_l$		–112.93 (83.07)	–146.02 (78.13)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_O$		–149.51 (126.10)	–182.13 (115.99)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_l$		27.10* (12.80)	17.63 (11.94)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j\Delta x_{jt}^{i}D_O$		0.90 (33.88)	0.75 (29.88)
R^2	0.079	0.032	0.107
Adjusted R^2	0.052	0.004	0.054

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations for each regression is 214. Heteroskedasticity-consistent standard errors are shown in parentheses. l, m, and h denote low-, medium-, and high-growth sectors. D_l is a dummy variable for developing countries. D_O is a dummy variable for OECD countries (including Greece). One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level.

Table 7. Country- and Time-Fixed Effects

Independent variable	Regression (1)	Regression (2)	Regression (3)
$\sum_{j} s_{jt}^{i}\gamma_j$	–8.19 (9.44)	3.16 (2.93)	–8.39 (9.42)
$\sum_{j \epsilon l} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	36.49 (50.82)	2.10 (87.77)	31.09 (67.33)
$\sum_{j \epsilon m} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	362.87** (92.72)	311.31** (83.09)	343.69** (97.28)
$\sum_{j \epsilon h} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	–6.85 (10.86)	–6.08 (9.38)	–6.44 (10.78)
Country-fixed effects	Yes	No	Yes
Time-fixed effects	No	Yes	Yes
F-test of no fixed effects	1.07	0.69	1.03
R^2	0.281	0.093	0.293
Adjusted R^2	0.077	0.057	0.070

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations for each regression is 214. Heteroskedasticity-consistent standard errors are shown in parentheses. One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level. The *F*-tests in regressions (1) and (2) test for the absence of country- and time-fixed effects, respectively. The *F*-test in regression (3) tests for the absence of both country- and time-fixed effects.

of fixed effects are absent. Introduction of fixed effects, especially country effects, leads to a considerable increase in the absolute value of the coefficient of the weighted-average-growth term and its standard error, and causes this coefficient to be insignificant.[17] The coefficient estimate of the medium-growth import variable, however, is not sensitive to the addition of fixed effects and remains significant in their presence.

Human capital could play an important role in the determination of productivity growth. To explore the influence of this factor, Table 8 experiments with a number of specifications that incorporate human capital, using the Bosworth, Collins, and Chen (1995) index based on educational levels of the labor force.[18] To allow human capital accumulation to exert an additional effect on productivity growth, regression (1) in Table 8 adds the annual rate of change in the human capital index to the model based on import variables. Regression (2) interacts the index (for each subperiod) with import variables to let the effect of openness depend on the level of human capital. Regression (3) includes the human capital

[17]This result indicates high multicollinearity between $\sum_j s_{jt}^{i}\gamma_j$ and country-fixed effects. Indeed, a regression of this variable on country dummy variables produces an R^2 equal to 0.91.

[18]An alternative index based on the proportion enrolled in secondary school (similar to the one used by Coe, Helpman, and Hoffmaister (1997)) was also tried but did not perform well.

Table 8. Adding Human Capital

Independent variable	Regression (1)	Regression (2)	Regression (3)
$\sum_{j} s_{jt}^{i}\gamma_j$	1.67** (0.58)	1.17336** (0.40)	1.64** (0.57)
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	5.42 (65.43)		
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	325.98** (76.21)		
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i}$	–6.70 (9.20)		
$\sum_{j\epsilon l} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i} H_t^i$		2.51 (55.77)	3.94 (51.48)
$\sum_{j\epsilon m} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i} H_t^i$		241.33** (53.06)	232.30** (50.97)
$\sum_{j\epsilon h} s_{jt}^{i}\gamma_j \Delta m_{jt}^{i} H_t^i$		–5.27 (6.20)	–5.30 (6.10)
$\Delta H_t^i / H_t^i$	–0.32 (0.30)		–0.32 (0.30)
R^2	0.082	0.082	0.086
Adjusted R^2	0.064	0.069	0.068

Source: See Data Appendix.

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations for each regression is 214. H is an index of human capital based on Bosworth, Collins, and Chen (1995). Heteroskedasticity-consistent standard errors are shown in parentheses. l, m, and h denote low-, medium-, and high-growth sectors. One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level.

index in both forms (i.e., the rate of change as well as the interaction terms). The results show that while the rate of change in human capital does not have a significant effect, the interaction of human capital with the import variables does marginally improve the performance of the model in terms of R^2.[19] However, even after allowing for a dependence on human capital, the effect of the import variable is significant only for sectors with medium growth.

We explore three further variations of the model. First, it is plausible to suppose that an increase in openness may take some time to bring about the transfer of technology and the import ratio may affect productivity growth with a time lag. Our data based on 3–5 year averages is not well suited for identifying a dynamic

[19]Results are not affected much if the rate of change in the human capital index is replaced by the level of the index in the regressions.

relation between openness and productivity growth. Nevertheless, we experimented with a number of specifications that included import variables or import ratios lagged one subperiod. Estimating regressions based on these specifications over the last four subperiods, we found the effect of lagged variables to be insignificant for all sectors.

Second, we consider the possibility that trade in one sector facilitates the transfer of technology in another. Although estimation of a general model that allows intersectoral effects to differ from one pair of sector to another is not feasible, we did explore a special model that assumes that the effects are the same for spillovers from one sector to another within each growth group as well as from each sector in one group to each sector in another.[20] Estimation of this particular model, however, did not suggest important intersectoral spillovers either within or between growth groups.

Third, we relax the assumption that the function $\phi_j(v^i_{jt})$ is linear. To account for a possible nonlinear relation in a simple way, three levels of the (within-sector) openness index are distinguished (on the basis of values at the beginning of each subperiod) and the coefficient of the trade variable, a_{2j}, is allowed to vary across these levels. The cutoffs for different levels of the openness index (as well as a_{2j}) are assumed to be the same within each growth group but are allowed to vary across the groups. The values of cutoffs (for different levels in each growth group) are estimated on the basis of the maximum likelihood criterion.[21]

Key results of this analysis are presented in Table 9, which shows estimates of a_{2j} for the three levels of each group, using the import measure of the trade index.[22] In the case of low- and high-growth groups, no level has a significant positive effect on productivity growth. All levels of the medium-growth group, however, exert a positive and significant effect, and there are significant differences between the effects of these levels. Interestingly, the effect of the medium level (representing the 0.3–0.5 range of m^i_{jt}) is greater than the effects of both low and high levels. The results suggest that there are increasing (spillover) returns to import competition at the low end of the openness index and diminishing returns at the higher end.

[20]Using the import measure, for example, the openness index for sector j can be generalized as

$$v^i_{jt} = \sum_k b_{jk} m^i_{kt},$$

where b_{jk} represents spillover effects both within and between sectors. The within-sector openness index (used in Tables 4–6) is a special case of this index with $b_{jk} = 1$ for $j = k$ and $b_{jk} = 0$ for $j \neq k$. A model based on the use of the above index in equation (7) involves estimation of a very large number of interaction terms $(s^i_{jt}\gamma_j \Delta m^i_{kt})$ and is thus difficult to implement. Letting l, m, and h represent low-, medium-, and high-growth groups, our special model assumes that $b_{jk} = b_{yz}$ for $j \varepsilon y$, $k \varepsilon z$, and $y, z = l, m, h$. This assumption allows aggregation of a number of interaction terms and thus significantly reduces the number of variables in the regression equation.

[21]The cutoffs were varied by increments of 0.1 to search for the values that maximize the log likelihood of the regression.

[22]We also estimated the nonlinear regression based on the export measure. Although the effect of the medium level in the high-growth group was significantly greater than zero in this regression, the hypothesis that all three levels have the same effect in each group (i.e., the $\phi_j(.)$ function is linear) could not be rejected.

Table 9. Exploring Nonlinearities

Independent variable	Estimated coefficient	Independent variable	Estimated coefficient
$\sum_j s_{jt}^i \gamma_j$	0.86* (0.43)	$\sum_{j \epsilon m} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{m2}$	1782.34** (527.16)
$\sum_{j \epsilon l} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{l1}$	0.62 (50.97)	$\sum_{j \epsilon m} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{m3}$	305.59** (89.41)
$\sum_{j \epsilon l} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{l2}$	–5748.83 (2991.63)	$\sum_{j \epsilon h} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{h1}$	153.27 (180.07)
$\sum_{j \epsilon l} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{l3}$	–566.45 (420.35)	$\sum_{j \epsilon h} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{h2}$	–81.37 (45.03)
$\sum_{j \epsilon m} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{m1}$	921.13* (460.46)	$\sum_{j \epsilon h} s_{jt}^i \gamma_j \Delta m_{jt}^i D_{h3}$	–2.44 (7.89)
F-test 1	2.96*		
F-test 2	4.61**		
F-test 3	1.58		
R^2	0.141		
Adjusted R^2	0.103		

Notes: The dependent variable is the aggregate TFP growth rate and the number of observations in the regression is 214.

Heteroskedasticity-consistent standard errors are shown in parentheses. l, m, and h denote low-, medium-, and high-growth sectors. D_{pq} are dummy variables equal to 1 if m_{jt}^i is at the qth level (q=1, 2, 3) of the pth growth group (p=l, m, h), and zero otherwise. The cutoffs for levels 1 and 2 are 0.8 and 0.9 for the low-growth group; 0.3 and 0.5 for the medium-growth group; and 0.2 and 0.7 for the high-growth group. One asterisk indicates that the coefficient is significantly different from zero at the 5 percent level and two asterisks, at the 1 percent level.

F-test 1 tests the hypothesis that the coefficients on the terms interacted by D_{lq} are jointly equal.
F-test 2 tests the hypothesis that the coefficients on the terms interacted by D_{mq} are jointly equal.
F-test 3 tests the hypothesis that the coefficients on the terms interacted by D_{hq} are jointly equal.

As sectoral trade and outputs are determined endogenously, a potential concern about the results is that they could reflect reverse causality running from aggregate productivity growth to changes in trade ratios.[23] There is no reason to expect, however, that causality in this direction would explain the main result that aggregate productivity growth is positively related to changes in import ratios for medium-growth sectors. Indeed, as discussed below, reverse causality is likely to produce the opposite result in the technology-gap model. Suppose, for example, that an increase in a developing country's productivity growth results from a uniform decrease in the technology lag for all sectors (for reasons other than increased openness). The technology-gap model would imply that the country's relative productivity gains would be greater for products with higher growth rates. This effect would tend to extend the comparative advantage of the country to higher-growth goods (in the middle range of the technology scale).[24] In this case, higher productivity growth would involve less imports and more home production for the medium-growth sectors and thus lead to (contrary to our results) a negative relation between productivity growth and changes in these sector's import ratios.[25]

Finally, it should be emphasized that the paper's classification of industries into three growth groups is based on the growth performance of broad (2-digit) manufacturing sectors. Data limitations did not permit us to use a grouping based on growth characteristics of more narrowly defined industries. Thus our growth groups are only suggestive and our empirical analysis should be thought of as identifying broad characteristics (rather than providing a precise list) of industries where openness improves productivity growth.

IV. Conclusions

This paper reexamines the role of international trade in determining productivity growth of developing countries, using a multisector framework based on the technology-gap model. A basic assumption of this framework is that sectors differ in their potential for long-run productivity growth. One implication of this assumption is that an increase in the share of high-growth sectors will raise overall productivity growth of an economy. This implication is supported by the paper's empirical analysis, which finds that a production-share weighted average of sectoral productivity growth rates (based on the experience of technological

[23]There has been much discussion about the problem of identifying the direction of causality between income per capita and the ratio of aggregate imports (or exports) to GDP. To deal with this problem, Frankel and Romer (1999) have used instrumental variables based on geographic characteristics of countries to identify a strong positive effect of trade on income. This approach, however, is not feasible for our model since geographic characteristics do not provide a good explanation of changes in sectoral trade ratios over time.

[24]Such a result is derived by Krugman (1985) using a Ricardian model with two countries and a continuum of goods.

[25]Even if the country were to experience uniform productivity growth in all sectors, there would be no presumption that such change would make it less competitive in (and hence increase the import ratio for) medium-growth sectors and thus account for our results.

leaders) is a significant determinant of the rate of aggregate productivity growth. It should be emphasized, however, that intersectoral differences in productivity growth rates as well as intercountry differences in sectoral shares are not very large and thus the weighted average of sectoral rates provides only a limited explanation of the cross-country variation in aggregate productivity growth.

An important issue investigated in the paper is whether the effect of increased openness on productivity growth varies across sectors. An interesting finding of the paper is that this effect depends on the growth potential of the sector. In low-growth (traditional) manufacturing sectors, increased international trade has little or no effect on productivity growth. For medium-growth sectors, however, greater import competition is found to have a significant growth-enhancing effect. There is also some evidence that export expansion in high-growth sectors leads to an increase in productivity growth.

The empirical literature on the influence of international trade on productivity growth in developing countries has been based largely on relations linking overall productivity growth to aggregate measures of openness. A key contribution of the present paper to this literature is to add a sectoral dimension to the productivity relation on the grounds that the impact of openness can differ from one sector to another. The paper's model could be tested directly by estimating sectoral relations that determine productivity growth in individual sectors. However, as data on productivity growth are available only at the aggregate level for most developing countries, this study develops and tests a relation that uses sectoral measures of openness to explain aggregate productivity growth.[26]

The evidence in the paper has interesting implications for trade policy in developing countries. For developing countries specialized in low-growth sectors, a case could be made for stimulating production in sectors with higher growth as a means to increasing overall productivity growth. The finding that increased import competition is an important source of technology transfer for medium-growth sectors suggests, however, that bringing about such a change through the imposition of import restrictions would not be desirable and could, in fact, impede growth.

DATA APPENDIX

Long-Run Sectoral Growth Rates

The source of these data for the 5 large countries (used to measure γ_j) as well as other OECD countries in Table 1 is the OECD's International Sectoral Database (ISDB). For each country, the long-run TFP growth rate for a sector was calculated simply as the average rate from 1970 to 1994 (excluding years where the data were missing). ISDB provided estimates of TFP

[26]Thus, an essential difference between our empirical relation and that of Coe, Helpman, and Hoffmaister (1997), for example, is that we use sectoral measures of openness while they employ aggregate measures. Also, since our relation is based on a different theoretical framework, we interact our openness index with a different variable (i.e., with long-run sectoral growth rates instead of foreign R&D stocks).

growth rates for the nine manufacturing sectors but not for total nonmanufacturing. ISDB data for individual nonmanufacturing sectors were aggregated to estimate TFP growth rates for total nonmanufacturing.

Sectoral Shares

These data were obtained from the UNIDO Industrial Statistics Database 1999 (Indstat3) and the UN's System of National Accounts (SNA). The Indstat3 provides value-added data for industries at the (ISIC Revision 2) 3-digit level. The data were aggregated to the 2-digit level to conform with the sectoral detail in the ISDB data used to obtain long-run sectoral TFP growth rates. For some years, Indstat3 combined certain 3-digit industries from different 2-digit groups and reported value added only for the combined group. In such cases, value added of individual industries was imputed on the assumption that their share (in total value added of the combined group) was the same as the share in a previous year (or the average share over a number of previous years). For some countries SNA data are reported for fiscal years and were adjusted to change the data to a calendar-year basis.

The aggregated Indstat3 data were used to calculate the value-added share of each 2-digit manufacturing sector in total manufacturing, $s^i_{j\,m}$. The SNA data were used to calculate the shares of manufacturing and nonmanufacturing value added in total value added, s^i_m and s^i_n, respectively. The share of each 2-digit manufacturing sector in total value added, s^i_j, was then calculated as the product of $s^i_{j\,m}$ and s^i_m. There were a number of gaps in both Indstat3 and SNA data series and the missing values of $s^i_{j\,m}$, s^i_m, and s^i_n had to be imputed or estimated. If the data were available for a year close to the missing-value year, the share for that year was used as a proxy. If no information was available for a year close by, the missing shares were estimated by regressions expressing shares as functions of time trend. The specification of the regression (for example, whether or not it includes the square of the time trend) was determined by comparing the R^2 of alternative regression specifications. There were no cases where both Indstat3 and SNA share series had to be imputed. The shares were only estimated for the years 1970, 1975, 1980, 1985, 1990, and 1993. The average shares for subperiods 1970–75, 1975–80, 1980–85, 1985–90, and 1990–93 were then calculated simply as averages of values at the beginning and the end of each subperiod.

Sectoral Import and Export Ratios

The trade data used for measuring these ratios were obtained from Feenstra, Lipsey, and Bowen (1997). They provide country data on manufacturing trade flows for 34 industries classified according to the Bureau of Economic Analysis Manufacturing Industry Classification. These data were aggregated into nine manufacturing categories matching the (2-digit) ISIC classification. Sectoral import and export ratios were estimated as follows. First, shares of sectoral imports and exports in nominal GDP were calculated using GDP data from the *World Economic Outlook*. These shares were then divided by sectoral production shares, s^i_j, to estimate x^i_j and m^i_j for manufacturing sectors. The difference between the values of these ratios at the beginning and the end of each subperiod were used to estimate Δx^i_j and Δm^i_j. These differences were then converted to annual changes. Since the trade data are only available up to 1992, the 1992 trade ratios were used as proxies for the 1993 ratios.

Aggregate TFP Growth Rates

The data on GDP, total stock of physical capital, and the total labor force needed to measure aggregate TFP growth were obtained from a revised version of the data set compiled by

Bosworth, Collins, and Chen. To make the TFP levels comparable across countries, the data on output and physical capital were converted into 1987 international prices using the purchasing power parities data from the Penn World Tables compiled by Summers and Heston. Following ISDB and Bosworth, Collins, and Chen, estimates of $\bar{g}_t^i$ were derived using the Cobb-Douglas production function and assuming uniform factor shares across countries. Two sets of estimates were used for factor shares. First, an estimate for the share of capital of 0.4 was used for all countries. Under this assumption, the aggregate TFP growth estimates for OECD countries calculated using the Bosworth, Collins, and Chen data were slightly lower than ISDB estimates. Therefore, in the regression analysis, the ISDB sectoral rates were adjusted downward to make the weighted average of these rates conform to the Bosworth, Collins, and Chen aggregate rate. Second, an estimate for the share of capital of 0.4 was used for developing countries and 0.3 for industrial countries. This variation did not significantly affect the regression results, therefore only the results from assuming capital shares of 0.4 across all countries are reported in the paper.

Human Capital Indexes

The data for the human capital indexes were obtained from the data set compiled by Bosworth, Collins, and Chen. They constructed the indexes by weighting data (obtained from Barro and Lee, 1993) on fractions of the population at different education levels by the relevant wage weights. The indexes for each subperiod (1970–75, 1975–80, 1980–85, 1985–90, and 1990–93), H_t^i, were calculated as simple averages of the indexes in the first and last year of each subperiod. The annual rate of change in the human capital index, $\Delta H_t^i / H_t^i$, was calculated as the change in the indexes over the first and last years of each subperiod divided by the index in the first year of each subperiod and then converted to an annual rate.

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