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Multinational enterprises, technology diffusion, and host country productivity growth

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Abstract

This paper investigates US multinational enterprises (MNEs) as a channel of international technology diffusion in 40 countries from 1966 to 1994. We use data on technology transfer to distinguish between the technology diffusion effect and other productivity-enhancing effects of MNEs. We find that the technology transfer provided by US MNEs contributes to the productivity growth in DCs but not in LDCs. We show that a country needs to reach a minimum human capital threshold level in order to benefit from the technology transfer of US MNEs; however, most LDCs do not meet this threshold requirement. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

International technology diffusion is the subject of many recent empirical studies.[1] In these studies, it is generally found that there exist significant cross-country knowledge spillovers in both disembodied and embodied forms. Interna-

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[1] See Helpman (1997) for a survey.

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tional trade and foreign direct investment (FDI) are considered to be two major channels for embodied knowledge spillovers. Although strong empirical evidence has been found supporting the importance of the trade channel, evidence regarding the FDI channel has been mixed. Using a multi-country framework, Lichtenberg and van Pottelsberghe de la Potterie (1996) found that inward FDI flows did not carry knowledge spillovers among OECD countries during the period 1970–1990, while Hejazi and Safarian (1996) found significant R&D spillovers in FDI from the US to other OECD countries during the same period. In a recent study, Borensztein, Gregorio, and Lee (1998, henceforth BGL) used data on FDI flow from OECD countries to 69 developing countries and found that FDI had a positive effect on per capita income growth only if the recipient country had reached a minimum human capital threshold. Single-country studies for Australia (Caves, 1974), for Canada (Globerman, 1979), and for Mexico (Blomström and Persson, 1983) found that the presence of multinational enterprises (MNEs) had positive effects on local productivity; however, studies for Morocco (Haddad and Harrison, 1993) and Venezuela (Aitken and Harrison, 1999) concluded that there was no evidence that MNEs had a positive effect on the productivity growth of local firms.

One important reason for the mixed results on FDI is that FDI data are of poor quality. Even within the OECD, countries define FDI differently. Moreover, FDI is a poor proxy for the magnitude of economic activities of MNEs. Therefore, one does not have much confidence in results from multi-country studies relying solely on FDI data. Some single-country studies have used better measures of the economic activities of MNEs (for example, value added or employment), but results from these studies are country-specific and difficult to generalize.

Another drawback of most earlier studies is that they fail to distinguish between the technology diffusion effect of MNEs and other productivity-enhancing effects. Some studies interpret a positive and statistically significant coefficient for the presence of MNEs (measured by MNE sales or FDI as a share of host country GDP) as indicating technology spillovers through MNEs. This interpretation is not correct, however, because the positive effect does not necessarily reflect technology diffusion by MNEs; it may simply indicate that the presence of MNEs increases competition in the host country and thereby leads to improved market efficiency and higher productivity.

This paper provides a multi-country study of the technology diffusion effect of MNEs. Our study differs from previous studies by using data on the technology transfer of MNE affiliates. We measure the technology transfer intensity of MNE affiliates by their spending on royalties and license fees as a share of their value added. Our assumption is that higher spending by the affiliates on technology transfer corresponds to greater technology diffusion to the host country.

The data we use are drawn from five surveys of US MNEs conducted by the Bureau of Economic Analysis (BEA) of the US Department of Commerce in 1966, 1977, 1982, 1989, and 1994. We restrict our sample to majority-owned affiliates of US MNEs in the manufacturing sector; these firms are generally believed to be the most relevant to the diffusion of advanced technology. The data allow us to construct a panel of four periods and 40 countries (20 DCs and 20 LDCs). While the sample covers fewer countries than some multi-country studies using FDI data, the estimates are more reliable due to better data quality. In addition, the results are more general than those from single-country studies.

To preview the main results, we find strong evidence regarding the impact of technology diffusion from US MNE affiliates in DCs, but weak evidence of this impact in LDCs. For the DC sample, we consider both technology diffusion by US affiliates and R&D spillovers from international trade. We find that the overall effect of technology spillovers through these two channels is to raise annual total factor productivity growth rate (GTFP) of DCs by 1.34 percentage points during the sample period. Of this overall effect, 40% is estimated to be attributable to the technology transfer of US affiliates. Our results suggest that MNEs are almost as important as international trade a conduit for technology spillovers among DCs.

For the LDC sample, we find evidence that US affiliates have positive effects on the productivity growth of the host country, but find no evidence that these positive effects are related to technology transfer. The underlying reason is that most LDCs do not have sufficient human capital to attract technology-intensive MNE affiliates and to absorb the technology diffused by MNEs. Our regression results show that the technology transfer of US MNEs enhances host country productivity growth only when the country has reached a human capital threshold somewhere between 1.4 and 2.4 years (in terms of male secondary school attainment). This threshold value is much higher than the 0.52 years estimated by BGL (1998). BGL's estimate is the human capital threshold to benefit from the presence of MNEs, while our estimate is the human capital threshold to benefit from technology transfer of MNEs. Most LDCs meet the first threshold but not the second. Our results are consistent with the findings of the previously mentioned single-country studies; technology spillover effects of MNEs are positive and significant in advanced countries but are insignificant in less developed countries.

We organize the remainder of the paper as follows. Section 2 specifies an empirical productivity growth equation that links host country productivity growth with technology transfer from MNEs. Section 3 describes the data, Section 4 describes regression results, and Section 5 concludes. Appendix A provides information regarding the construction of the data set.

2. Empirical specification

This section discusses the empirical specification used in this study. We specify a panel data regression equation as follows:

$$\mathrm{GTFP}_{it} = a_i^0 + a_t^0 + a_1 \mathrm{GAP}_{it} + a_2 H_{it} + a_3 \mathrm{MNE}_{it} + \varepsilon_{it}, \tag{1}$$

where $GTFP_{it}$ is the growth rate of total factor productivity (TFP) of country i at time t, a_i^0 is a country-specific constant, a_t^0 is a time-specific constant, GAP is the technology gap measured by TFP of the country relative to TFP of the US, H is the human capital level of the country, MNE is a measure of the activities of MNE affiliates that affect host country productivity growth, and ε is an error term.

We use existing models in the literature to justify Eq. (1). For example, consider the technology diffusion model of Barro and Sala-i-Martin (1997).[2] The model has a technologically leading country that innovates new technologies, and a follower country that imitates the technologies. Let N_1 and N_2 be the technology stocks of the leading country and the follower country, respectively. The follower country can select for imitation only from the uncopied subset of the leading country's technology stock. Given that the technologies that are easier to imitate are copied first, the cost of imitation rises as N_2 increases relative to N_1. This implies that the rate of imitation decreases with N_2/N_1. Since the follower country's productivity growth is determined by the rate of imitation, it also decreases with N_2/N_1. In Eq. (1), we measure the technology gap N_2/N_1 by the variable GAP. Barro and Sala-i-Martin (1997) showed that different countries have different steady states. In Eq. (1), we use country- and time-specific constants to control for steady-state differences.

New technologies of the leading country do not impact the follower country's TFP automatically. As emphasized by Nelson and Phelps (1966) and empirically verified by Benhabib and Spiegel (1994), a country's human capital level determines its capacity to absorb advanced technology. In Eq. (1), we include the variable H (measured by average years of male secondary school attainment in the population over age 25) to capture this effect.

New technologies are diffused through a variety of channels, including MNEs. Findlay (1978) presented a model in which the rate of technical progress in a developing country was hypothesized to be an increasing function of both the technology gap and the share of FDI in the capital stock.[3] Several empirical studies mentioned in the introduction used the FDI/GDP ratio to estimate the effects of MNEs on host country productivity growth. The problem with this measure is that it does not distinguish between the technology diffusion effect of MNEs and other productivity-enhancing effects.

Our study attempts to estimate the technology diffusion effect of MNEs. The immediate issue is to find a measure that captures this effect. We assume that MNEs must incur technology transfer costs in order to apply new technologies in a

[2] See also Howitt (1998) and Jones (1998, Chap. 6).

[3] See Wang (1990) for an extension of Findlay (1978), and Wang and Blomström (1992) for a game-theoretic model of MNEs that provides some microeconomic foundations for the hypothesis that the rate of technical progress in a developing country increases with the share of FDI in capital stock.

country.[4] Thus, the expenditure of MNE affiliates on technology transfer conveys useful information on the amount of new technologies used in the country by these affiliates. The technologies of MNE affiliates are exposed to local researchers through patent documents, local production, and the workers they hire. If part of the transferred technologies end up in the public domain of the host country and are absorbed by local researchers, then we would expect a positive effect on the productivity growth of the host country, which is what we refer to as the technology diffusion effect of MNEs.

Based on the above discussion, we construct three measures for the variable MNE in Eq. (1):

YM ≡ value added of MNE affiliates/host country GDP,
TR ≡ technology transfer spending of MNE affiliates/value added of MNE affiliates,
YM * TR ≡ technology transfer spending of MNE affiliates/host country GDP.

By substituting each of these three measures into Eq. (1), we obtain three regression equations.

We will use 2SLS method to estimate Eq. (1), using instrumental variables for YM and TR. We will view a positive and statistically significant coefficient for YM as evidence that the presence of MNEs enhances the host country's TFP growth, and a positive and statistically significant coefficient for TR as evidence that the technology transfer of MNEs enhances the host country's TFP growth. We estimate the technology diffusion effect of MNEs by using the variable YM * TR, which measures MNE technology transfers as a percent of the host country's GDP.

3. Data

We use data from five benchmark surveys of MNEs and their foreign affiliates conducted by the BEA of the US Department of Commerce in 1966, 1977, 1982, 1989, and 1994.[5] For a multi-country study on MNEs, we believe these surveys provide the data with the highest quality possible. The data set we construct contains 40 countries and is organized in four time periods. We include in the data set only majority-owned affiliates in the manufacturing sector since they are the most relevant for studying technology diffusion. Table 1 presents some statistics of US manufacturing affiliates in the 40 countries.

[4] Teece (1977) examined the cost of technology transfer across countries for MNEs. For 26 cases in chemicals, petroleum refining, and machinery, he found that the cost averaged 19% of total project expenditures.

[5] BEA also conducts annual surveys of MNEs, but the data needed for this study are available only in these benchmark surveys.

Table 1
Statistics of majority-owned affiliates of US manufacturing MNEs
YM = value added of affiliates/host country GDP, TR = royalties and license fees paid by affiliates/value added of affiliates.

	YM		TR	
	(1982–1989)	(1989–1994)	(1982–1989)	(1989–1994)
Canada	0.054	0.049	0.024	0.029
Costa Rica	0.022	0.021	na	0.017
Dominican Republic	0.005	0.007	na	na
Mexico	0.018	0.021	0.028	0.037
Argentina	0.017	0.010	0.010	0.013
Brazil	0.033	0.028	0.001	0.002
Chile	0.008	0.013	0.007	0.006
Colombia	0.017	0.015	na	0.005
Ecuador	0.005	0.004	0.028	na
Peru	0.004	0.003	na	0.018
Venezuela	0.015	0.014	0.004	0.011
Hong Kong	0.009	0.011	0.039	0.046
India	0.001	0.001	0.016	0.018
Israel	0.004	na	0.012	na
Japan	0.002	0.003	0.158	0.169
Korea	0.002	0.002	0.048	na
Malaysia	0.013	0.016	0.014	0.016
Philippines	0.013	0.015	0.020	0.029
Singapore	0.043	0.049	0.057	na
Taiwan	0.010	0.008	0.019	0.021
Thailand	0.004	0.006	0.029	0.025
Austria	0.005	0.006	na	na
Belgium	0.030	0.031	0.037	0.037
Denmark	0.004	0.004	0.020	0.019
Finland	na	0.001	na	na
France	0.013	0.012	0.056	0.062
Germany	0.023	0.018	0.033	0.044
Greece	0.004	0.004	0.008	0.011
Ireland	0.081	0.093	0.042	0.095
Italy	0.009	0.008	0.061	0.072
Netherlands	0.025	0.028	0.065	0.076
Norway	0.002	0.002	0.018	0.027
Portugal	0.007	0.007	0.041	0.029
Spain	0.013	0.013	0.034	0.026
Sweden	0.006	0.005	0.097	0.075
Switzerland	0.007	0.007	0.021	0.031
Turkey	0.001	0.002	na	0.015
UK	0.034	0.029	0.034	0.047
Australia	0.024	0.020	0.017	0.023
New Zealand	0.009	0.007	0.015	0.019

Table 2
Summary statistics, 1966–1994
GTFP = annual growth rate of total factor productivity; GAP = host country TFP/US TFP, initial year; H = male secondary school attainment in the population over age 25; YM = value added of affiliates/host country GDP; TR = royalties and license fees paid by affiliates/valued added of affiliates; YM∗TR = the product of YM and TR multiplied by 100; GSF = annual growth rate of foreign R&D spillovers in trade flows.

Variable	Full sample		DC sample		LDC sample	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
GTFP	0.004	0.022	0.004	0.016	0.004	0.027
GAP	0.586	0.200	0.720	0.110	0.444	0.174
H	2.001	1.135	2.711	1.077	1.447	0.834
YM	0.014	0.015	0.018	0.020	0.011	0.010
TR	0.034	0.031	0.043	0.034	0.024	0.023
YM∗TR	0.052	0.093	0.074	0.117	0.025	0.038
GSF	na	na	0.039	0.029	na	na

The presence of MNEs in a country (YM) is measured by the share of the affiliates' value added in host country GDP. Over the period 1966–1994, value added of US manufacturing affiliates accounted for 1.4% of host country GDP in the sample (1.8% for the DC sample and 1.1% for the LDC sample). As Table 1 indicates, the value of YM varies considerably across countries in the sample.

We construct a variable of technology transfer intensity (TR), which is measured by the affiliates' spending on royalties and license fees as a share of their value added.[6] The sample average of this share is 3.4%. The data show that technology transfer intensity is significantly higher for affiliates in DCs (4.3%) than for those in LDCs (2.4%).

The variable YM∗TR reflects the interaction of the presence of MNEs with technology transfer intensity. This variable is equal to the affiliates' spending on technology transfer as a share of host country GDP. Our assumption is that higher spending by MNEs on technology transfer corresponds to greater technology diffusion to the host country. Therefore, the variable YM∗TR is our preferred measure of the technology diffusion effect of MNEs.

Our study also draws data from the Penn World Tables (PWT, Mark 5.6) and other sources. Table 2 provides summary statistics of the variables for the full sample and for the DC and LDC samples, respectively. Details regarding the construction of the data set are provided in Appendix A.

[6] Royalties and license fees arise from licensing agreements that are received by licensers in return for providing licensees with access to a particular technology. The technology transferred may include trademarks, copyrights, patents, know-how (e.g., designs, formulas, industrial processes, and other unpatented private technology), or any combination of the above.

4. Empirical findings

Tables 3–5 present results from panel data regressions. The data for the 40 countries and the four periods are pooled and country- and time-specific constants are used. The dependent variable is the average annual growth rate of TFP. The estimation uses the 2SLS method. To deal with the endogeneity of YM, we first regress YM against lagged YM and other exogenous variables, and then use the predicted value of YM from this regression as the instrument for YM.[7] Similarly, we use the predicted value of TR as the instrument for TR.

Table 3 reports results from the full sample. Notice first that the coefficient for the technology gap variable (GAP) is negative and statistically significant in all regressions, indicating the existence of a catch-up effect. Human capital (H) is measured by male secondary school attainment. Coefficients for this variable are significant only in regression (3.1); hence, we drop it from the other regressions. A statistically insignificant coefficient on H does not necessarily imply that H has no effect on TFP growth. We find that H is highly correlated with country-specific dummies and therefore its effect is captured by the country-specific intercepts.[8] Moreover, H affects TFP growth indirectly through TR, as will be shown in Table 6.

Regression (3.1) includes YM, which is MNE affiliates' value added as a proportion of the host country's GDP. The coefficient for YM is found to be positive and statistically significant. This result shows that the presence of MNEs enhances the host country's productivity growth. The positive effect is not necessarily due to technology spillovers via MNEs, however, since local productivity may be enhanced simply as a result of increased competition due to the presence of MNEs.

Regression (3.2) includes TR, the spending of MNE affiliates on royalties and license fees as a share of their value added.[9] The coefficient for TR is found to be positive and statistically significant. This result shows that the technology transfer intensity of MNE affiliates is important for host country productivity growth.

[7] We believe the lagged YM is satisfactory as an instrumental variable for two reasons. First, the error term in the productivity growth equation displays little serial correlation. In fact, the productivity growth rate itself is not serially correlated; the correlations of the TFP growth rates between the four periods in our sample are 0.06, 0.29, and 0.12, respectively. This implies that the lagged YM has a low correlation with the error term of the productivity growth equation. Second, the lagged YM is highly correlated with the current YM. The regression of YM on lagged YM and other exogenous variables has an R^2 of 0.966.

[8] In the sample, country-specific dummies explain 81% of the variation in human capital.

[9] The sample size falls from 122 to 90 because data on TR are not available for some countries in certain periods.

Table 3
Regression results for TFP growth, panel data, full sample, 2SLS
All equations include unreported time- and country-specific constants. The dependent variable is GTFP over four periods: 1966–1977, 1977–1982, 1982–1989, and 1989–1994. YM and TR are instrumented. DC and LDC are dummy variables for developed and developing countries, respectively. See Table 2 for definitions of other variables. Numbers in parentheses are t-statistics.

Regression number	3.1	3.2	3.3	3.4
GAP	−0.121	−0.177	−0.147	−0.138
	(−4.156)**	(−5.132)**	(−4.837)**	(−3.427)**
H	0.019			
	(3.322)**			
YM	0.771			
	(2.510)**			
TR		0.802		
		(2.335)**		
YM∗TR			0.067	
			(2.446)**	
YM∗TR∗DC				0.066
				(1.850)*
YM∗TR∗LDC				−1.674
				(−0.916)
R^2	0.574	0.686	0.682	0.473
R^2 adjusted	0.339	0.483	0.475	0.116
Standard error	0.016	0.014	0.014	0.018
Number of observations	122	90	90	90

* Significant at the 10% level.
** Significant at the 5% level.

Regression (3.3) includes YM∗TR, the product of YM and TR multiplied by 100. YM∗TR captures the magnitude of MNE technology diffusion, as measured by technology transfer spending of MNE affiliates as a share of host country GDP.[10] Regression (3.3) shows that the coefficient for YM∗TR is positive and statistically significant. We believe this is evidence that US manufacturing MNEs transmitted technology to their host countries during the sample period. The point estimate 0.067 implies that the absence of the technology transfer of US manufacturing MNE affiliates would reduce annual TFP growth rates of the host countries in the sample by an average of 0.35 percentage points.[11]

[10] Note that YM∗TR captures only MNE technology transfers; it does not capture MNE presence. Including both YM and TR separately in the regression would capture both MNE presence and MNE technology transfers. We have run such a regression and found that both variables have positive coefficients; TR enters significantly (t-value = 2.134) and YM enters insignificantly (t-value = 1.020).

[11] Table 2 reports that the sample mean of YM∗TR is 0.052. Therefore, the technology diffusion effect of MNEs on host country TFP growth is $0.052*0.067=0.0035$, according to regression (3.3).

Table 4
Regression results for TFP growth in OECD countries, panel data, 2SLS
All equations include unreported time- and country-specific constants. The dependent variable is GTFP over four periods: 1966–1977, 1977–1982, 1982–1989, and 1989–1994. YM and TR are instrumented. See Table 2 for definitions of variables. Numbers in parentheses are t-statistics.

Regression number	4.1	4.2	4.3	4.4
GAP	−0.117	−0.199	−0.126	−0.110
	(−3.154)**	(−3.381)**	(−2.856)**	(−2.653)**
YM	0.686			
	(3.087)**			
TR		0.941		
		(2.819)**		
YM∗TR			0.067	0.073
			(3.176)**	(3.695)**
GSF				0.206
				(2.616)**
R^2	0.624	0.607	0.679	0.732
R^2 adjusted	0.432	0.373	0.489	0.560
Standard error	0.011	0.012	0.010	0.010
Number of observations	69	60	60	60

** Significant at the 5% level.

Regression (3.4) interacts YM∗TR with dummies for developed and less developed countries. The results show that YM∗TR has a statistically significant effect on productivity growth in DCs, but not in LDCs. These results suggest that

Table 5
Regression results for TFP growth in LDCs, panel data, 2SLS
All equations include unreported time- and country-specific constants. The dependent variable is GTFP over four periods: 1966–1977, 1977–1982, 1982–1989, and 1989–1994. YM and TR are instrumented. See Table 2 for definitions of variables. Numbers in parentheses are t-statistics.

Regression number	5.1	5.2	5.3
GAP	−0.212 (−3.889)**	−0.184 (−3.823)**	−0.190 (−4.105)**
YM	3.109 (1.828)*		
TR		2.032 (1.030)	
YM∗TR			0.065 (0.036)
R^2	0.640	0.825	0.837
R^2 adjusted	0.332	0.577	0.606
Standard error	0.021	0.017	0.016
Number of observations	53	30	30

* Significant at the 10% level
** Significant at the 5% level.

Table 6
Regression results for technology transfer intensity of MNEs, panel data, OLS
All equations include unreported time- and country-specific constants. The dependent variable is TR over four periods: 1966–1977, 1977–1982, 1982–1989, and 1989–1994. YM(−1) is lagged value of YM. See Table 2 for definitions of variables. Numbers in parentheses are *t*-statistics.

	Regression number		
	6.1	6.2	6.3
	Full sample	DC sample	LDC sample
GAP	0.031 (2.348)**	0.073 (2.191)**	−0.003 (−0.427)
H	0.008 (2.735)**	0.004 (1.352)	0.008 (2.212)**
YM(−1)	0.809 (4.249)**	0.768 (4.004)**	−1.163 (−2.071)*
R^2	0.954	0.957	0.947
R^2 adjusted	0.923	0.930	0.866
Standard error	0.009	0.009	0.004
Number of observations	92	61	31

*Significant at the 10% level.
**Significant at the 5% level.

the full sample may disguise differences between DCs and LDCs regarding the effects of MNEs. Thus, it is useful to investigate DCs and LDCs separately.

Table 4 presents results from the DC sample. Regressions (4.1)–(4.3) are the same as regressions (3.1)–(3.3) except that they are applied to the DC sample. We find that the estimated effects of MNEs are similar to the full sample, which may imply that the results from the full sample are largely driven by developed countries.

Regression (4.4) includes a new variable GSF, the growth rate of foreign R&D spillovers in trade flows. This variable is based on a measure constructed by Coe and Helpman (1995). The Coe–Helpman measure of foreign R&D spillovers in country i is defined as $\mathrm{SF}_i = \sum_{j \neq i}(M_{ij}/M_i)\mathrm{SD}_j$, where SD_j denotes domestic R&D stock of country j, M_{ij} is the value of imports from country j to country i, and $M_i = \sum_{j \neq i} M_{ij}$. According to this measure, foreign R&D spillovers in trade flows are proxied by the bilateral-imports-share-weighted sum of R&D capital stocks of trade partners.[12]

[12] The Coe–Helpman approach was criticized by Keller (1998), who found that spillovers constructed with randomly created trade data explain more of the productivity variation than the CH spillover measure constructed with total import data. Xu and Wang (1999) showed, however, that the CH measure outperforms Keller's measure when capital goods import data are used instead of total imports data. See also Lichtenberg and van Pottelsberghe de la Potterie (1998) and Coe and Hoffmaister (1999).

Regression (4.4) shows that the estimated coefficients for both YM ∗ TR and GSF are positive and statistically significant.[13] This result is interesting because it shows that MNEs and international trade are simultaneous channels of international technology diffusion. Over the sample period, the mean of GSF is 3.9% (see Table 2); since the coefficient for GSF is 0.206, a growth rate of 3.9% implies an increase in annual TFP growth rate by $3.9 * 0.206 = 0.80$ percentage points. Over the sample period, the mean of YM ∗ TR is 7.4% for DCs (see Table 2); since the coefficient for YM ∗ TR is 0.073, the absence of the technology transfer of US manufacturing affiliates would reduce annual TFP growth rate by $7.4 * 0.073 = 0.54$ percentage points. Thus, the overall effect of the technology transmitted via both trade and US manufacturing affiliates was to raise annual TFP growth rate of DCs by $0.80 + 0.54 = 1.34$ percentage points.[14] Of this overall effect, 40% (0.54/1.34) was due to U.S manufacturing affiliates. These estimates suggest that MNEs are almost as important as international trade a conduit for technology spillovers among DCs.

Table 5 presents results from the LDC sample. Regressions (5.1)–(5.3) are the same as regressions (4.1)–(4.3) except that they are applied to the LDC sample. Regression (5.1) shows that the coefficient for YM is positive and statistically significant, indicating that the presence of US manufacturing affiliates enhanced TFP growth for LDCs in the sample. Regression (5.2) shows that the coefficient for TR, the technology transfer intensity of US MNE affiliates, is positive but statistically insignificant. Regression (5.3) shows that the coefficient for YM ∗ TR, the measure of technology diffusion from US affiliates, is positive but statistically insignificant. Results from these last two regressions indicate that the technology diffusion effect of MNEs is not statistically significant in the LDC sample; this contrasts sharply with the results from the DC sample.[15]

Our findings raise an important question: Why do US MNEs have a technology diffusion effect on TFP growth in DCs but not in LDCs? In what follows, we present an argument that human capital is the key to answering this question. First, we observe from Table 2 that the average male secondary school attainment in the

[13] Coe and Helpman (1995) also include domestic R&D capital stock in their TFP regressions. The growth rates of domestic R&D capital stock do not enter regression (4.4) significantly, however. The reason may be that variations in the growth rates of domestic R&D capital stocks are absorbed in country-specific constants. Country dummies explain 88% of the variations in the growth rates of domestic R&D capital stocks. By contrast, country dummies explain only 16% of the variations in GSF, which allows us to separately estimate its effect on TFP growth.

[14] It should be noted that these growth effects are obtained after controlling for the technology gap; hence they reflect short-run effects, not long-run effects. The powerful negative effect of GAP implies that the growth effects of MNEs and trade will decrease as the technology gap narrows over time.

[15] A comparison between regressions (4.1)–(4.3) and regressions (5.1) and (5.3) shows clearly that there exist structural differences between the models estimated for the DC and LDC samples. *F*-tests cause us to reject the hypothesis that the coefficients in the LDC regressions are the same as those in the DC regressions.

sample period is 2.7 years in DCs but only 1.4 years in LDCs. Second, we find that the level of human capital determines the intensity of technology transfer by US MNEs. In Table 6, we report regressions of TR with respect to H and other variables. The coefficient for H is positive and statistically significant for the full sample and the LDC sample. This result indicates that human capital is an important element in attracting technology transfer from MNEs, especially in developing countries. Results from Table 6 help explain why the technology transfer intensity of US MNEs is significantly lower in LDCs than in DCs.[16] A low technology transfer intensity of MNEs limits them as a source of technology diffusion. This partially explains why the technology diffusion effect of MNEs is weak in the LDC sample.

Although the technology transfer intensity of MNEs in LDCs is relatively low, it is positive and one would still expect technology diffusion to have some impact. The fact that we do not detect an impact in the LDC sample suggests that something else is in play. In Eq. (1), we did not consider the interaction between the H and MNE variables. BGL (1998) developed a model in which H has a non-linear effect on economic growth; the growth effect of FDI is positive only if H is above a threshold level. Since MNEs generally use technology at a higher level than local firms in LDCs,[17] the absorption of MNE technology may require a relatively high level of human capital. These results suggest that a minimum level of human capital may be required before a country can benefit from technology spillovers from MNEs.

To gauge this minimum level of human capital, we run regressions using samples selected according to different human capital thresholds. The results are presented in Table 7. We find that the coefficient for $YM*TR$ is negative and statistically insignificant when the sample includes only countries whose H value is below 1.3. When the sample includes countries with H values between 1.3 and 2.3, $YM*TR$ has a positive but statistically insignificant effect on TFP growth. When the sample includes countries with H values above 2.3, the positive effect of $YM*TR$ becomes statistically significant.[18] Although these regressions do not yield a precise estimate of the human capital threshold needed for technology transfers to have a significant effect on a host country's TFP growth, they suggest

[16] Table 2 shows that technology transfer intensity is significantly lower for MNE affiliates in LDCs (2.4%) than for those in DCs (4.3%). Using data on R&D spending of US manufacturing affiliates in the period 1982–1994, we find that R&D intensity is also significantly lower for MNE affiliates in LDCs (1.3%) than for those in DCs (3.4%).

[17] According to Graham and Krugman (1991), foreign firms need to have a technology advantage in order to offset the advantages enjoyed by local firms in terms of better knowledge and access to domestic markets.

[18] Notice that as we include countries with higher H values in the regressions, the estimated coefficients for $YM*TR$ decline, which seems to suggest diminishing marginal benefits from MNE technology transfers.

Table 7
Regression results for identifying human capital threshold, panel data, 2SLS
All equations use the specification of regression (3.3). Sample is selected based on the human capital threshold specified in the first column.

Sample ($\hat{H}$)	YM ∗ TR coefficient	YM ∗ TR t-statistic	Adjusted R^2	Number of observations
< 1.3	−0.177	−0.130	0.448	21
< 1.4	0.935	1.041	0.419	24
< 1.5	0.881	1.296	0.542	28
< 1.6	0.819	1.177	0.492	30
< 1.7	0.683	1.186	0.485	32
< 1.8	0.683	1.186	0.496	33
< 1.9	0.727	1.401	0.489	36
< 2.0	0.727	1.401	0.478	37
< 2.1	0.727	1.401	0.466	38
< 2.2	0.730	1.410	0.427	41
< 2.3	0.730	1.410	0.427	41
< 2.4	0.800	2.244**	0.450	47
< 2.5	0.756	2.422**	0.475	49
< 2.6	0.186	1.837*	0.365	54
< 2.7	0.178	1.790*	0.372	55
< 2.8	0.157	1.508†	0.333	57
< 2.9	0.158	1.583†	0.394	61
< 3.0	0.052	1.781*	0.399	64
< 3.1	0.052	1.872*	0.419	69
< 3.2	0.051	1.855*	0.427	70

* Significant at the 10% level.
** Significant at the 5% level.
† Significant at the 15% level.

that such a threshold exists and is somewhere between 1.4 and 2.4 years (in terms of male secondary school attainment).[19]

An estimated human capital threshold value of around 1.9 (the middle point between 1.4 and 2.4) explains why the technology diffusion effect is statistically insignificant in the LDC sample. Of the 30 observations used to estimate regressions (5.2) and (5.3), only five exceed the threshold value.[20] It is useful to compare our estimate of the threshold value with that reported by BGL (1998). Using data on FDI flows from industrial countries to 69 developing countries from

[19] This is the interval in which the estimated effect of YM ∗ TR turns from positive and statistically insignificant to positive and statistically significant. Following the method of BGL (1998), we estimated a threshold equal to 2 from a regression with an interaction term between H and YM ∗ TR. We favor the method shown in Table 7 over the BGL approach because it is less restrictive and more convincing.

[20] They are Hong Kong (1982–1989, 1989–1994), Israel (1982–1989), and Taiwan (1982–1989, 1989–1994).

1970 to 1989, BGL (1998) found that FDI contributed to economic growth only when the host country had human capital values above 0.52 years of male secondary school attainment. For the threshold value estimated by BGL, LDCs would be expected to benefit from the *presence* of MNEs. Our regression (5.1) shows that the presence of MNEs does have a positive and statistically significant effect on TFP growth.[21] By distinguishing the technology diffusion effect from other productivity-enhancing effects of MNEs, our study shows that a much higher human capital threshold is required for LDCs to benefit from the technology transfer of MNEs. This threshold value is not met in most LDCs.

Our results are consistent with the findings of several single-country studies (e.g., the ones mentioned in the introduction). These studies find that technology spillover effects of MNEs are positive in advanced countries such as Australia and Canada and are statistically insignificant in less developed countries such as Morocco and Venezuela.

5. Conclusion

This paper investigated the hypothesis that MNEs are an important channel of international technology diffusion. Our investigation used data on majority-owned affiliates of US manufacturing MNEs in 40 countries covering the period 1966–1994. A distinctive feature of our study was to distinguish between the technology diffusion effect and other productivity-enhancing effects of MNEs.

The paper found strong evidence of technology diffusion from US MNE affiliates in DCs, but weak evidence of such diffusion in LDCs. Results from the DC sample indicated that US MNEs are almost as important as international trade a conduit for technology spillovers. In the sample period, the overall effect of technology spillovers through these two channels was found to raise annual TFP rate of DCs by 1.34 percentage points. Of this overall effect, 40% was attributable to the technology transfer of US affiliates.

The paper found that the level of human capital is crucial for a country to benefit from the technology spillovers of MNEs. It was found that a country needs to reach a human capital threshold of about 1.9 years (in terms of male secondary school attainment) to benefit from technology transfer of US MNE affiliates, which is much higher than the threshold of 0.52 years estimated by BGL (1998) for a country to benefit from the presence of MNEs. Most LDCs meet the second threshold but not the first. Our results are consistent with the findings of single-country studies that the technology spillover effects of MNEs are positive in advanced countries but are insignificant in less developed countries.

[21] Regression (5.1) uses observations from 12 countries: Mexico, Argentina, Chile, Colombia, Peru, Venezuela, Hong Kong, India, Israel, Philippines, Taiwan, and Thailand. All observations have H above 0.52 except India during 1966–1977.

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Appendix A

Data on foreign affiliates of MNEs are from *US Direct Investment Abroad, Benchmark Survey* in 1966, 1977, 1982, 1989, and 1994. MNE affiliates in our sample are majority-owned affiliates of non-bank US parents in the manufacturing sector. Royalties and license fees are gross payments by the affiliates to parents. Data are organized in four periods, 1966–1977, 1977–1982, 1982–1989, and 1989–1994. Average annual growth rate of variable X over Δt is calculated according to $GX = (\ln X_{t+\Delta t} - \ln X_t)/\Delta t$. Averaged value of variable X over Δt is the average of X_s, $s \in \Delta t$, and $X_s = X_t(1+GX)^{s-t}$.

TFP is calculated based on data in the PWT (Mark 5.6). $\mathrm{TFP}_{it} = \mathrm{Y}_{it}/(K_{it}^{0.35} L_{it}^{0.65})$, where i and t are country index and time index, respectively; Y is real GDP in 1985 international prices; K is capital stock including plant and equipment, non-residential construction and other construction (in 1985 international prices); and L is labor force in thousands. Because PWT data are available only through 1992, the average annual growth rate of TFP for 1989–1992 is used for the period 1989–1994 in our sample.

The technology gap is measured by TFP relative to US TFP in the initial year. Human capital is measured as average years of male secondary school attainment in the population over age 25, taken from Barro and Lee (1996) and available for 1965, 1970, 1975, 1980, 1985, and 1990; data for the four periods in our sample are the average over 1965–1975, 1975–1980, 1980–1985, and 1985–1990. Foreign R&D spillovers in trade flows are measured as bilateral-imports-share-weighted sum of R&D capital stocks of trade partners (data are from Coe and Helpman, 1995).

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