TRADE, THE CHANNEL OF INNOVATION: A NETWORK EXPLANATION ON TECHNOLOGY SPILLOVERS

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ABSTRACT

This paper attempts to propose a more sophisticated model that addresses the structural trade mechanisms for technology spillovers across nations. This paper connects two separate models by applying network estimations representing knowledge diffusion to the Coe and Helpman model of international R&D spillovers. The results of panel analysis from 1971 to 2000 on 24 OECD countries validate that the network estimator of effective size performs much better than Coe and Helpman's estimation - the bilateral-import-share-weighted for foreign R&D capital. These findings offer policy implications that help how to decide trade partners and organize them for effective absorption or creation of knowledge. Lastly, as the supplementary analysis, the model is applied to 24 non OECD countries. Due to the data limitation, it failed to compare the validity of explanatory estimators, but the result shows that international technology spillovers is the crucial to increase productivity, even more than domestic R&D expenditure in developing countries.

Keywords: *trade networks, technology spillovers, effective size, innovation.*

1.0 INTRODUCTION

The trump of East Asian economic growth and the trap of African countries poverty since the 1960s throw a big question mark on exogenous growth theory. The Solow model adopted by majority of economists proves the positive correlation between investment and level of growth per capital income. This model also finds diminished returns under the assumption of exogenous technology. It infers that the determinant conditions for investment are given endowments such as labor, capital, and natural resources or technology. However, endogeneity could also emerge in the existence of the interactional effect between technology and its channel of diffusion. This is because technology for rival or non rival goods can be a by-product that invisibly flows through any kind of socio-economic exchange.

The endogenous growth model tackles the issue of endogenous conditions of technology. Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992) emphasize the 'idea' that springs from research and development (R&D) investment. The new ideas improve productivity once they are embodied in non-labor inputs such as higher quality intermediate goods. Therefore, investment activities directly affect the creation of ideas. Indirect effects of R&D in other places are also accrued when industries in other sectors, or other countries, buy intermediate goods from industries conducting R&D.

By accepting of technology spillovers at the international level, the endogenous growth theory also brought new implications to trade. The traditional literature emphasizes gains from trade that stem from comparative advantage. This advantage is derived from exogenously given technology differences or factor endowments. However, endogenous theorists shed light on the benefits of learning occurred in trade. "Foreign trade boosts domestic productivity: by making available products that embody foreign knowledge and by making availability useful information that would otherwise be costly to acquire. Both are particularly important for less developed countries that lag far behind the technology frontier" (Coe *et.al*., 1995).

Nadiri (1994) and Erk, Ates, and Tuncer (2000) specify the channels of technology diffusion driven by international trade: 1) international trade and the foreign direct investment (FDI) provide opportunities for cross-border learning in the normal course of business, which requires no special effort or investment of resources, 2) it enables imported nations to imitate foreign products and methods. In particular, the role of trade is very important for the fastest growing economies that rely on imitation extensively, such as Japan in the immediate postwar era and newly industrialized economies (NIEs) more recently. 3) International trade and the FDI reduce innovation and imitation costs, making it easier for developing countries to raise total factor productivity in the future.[1]

Although the relationships made by trade and their effects on technology diffusion were emphasized, the trade network mechanism at the international level has rarely been studied. Instead of the diffusion mechanism by trade, empirical case studies or theoretical attempts

[1] What makes this analysis meaningful is that technology diffusion conditional to trade pattern also holds one of the keys to interpret different trajectories of development among developing countries.

using econometric models have been conducted to prove the existence of technology diffusion through trade channels. Following Gene Grossman, Elhanan Helpman and David T. Coe, the founders of this line of research, Rivera-Batiz and Romer (1991), Blomstrom, Lipsey and Zejan (1992), and Romer (1993) focused on international trade to examine knowledge diffusion and accumulation due to its role in facilitating technology transfers among countries. A common feature among the earlier literature simply emphasized the "facilitation" function of international trade rather than how the imitation and absorption of new technology processes (Grossman and Helpman, 1991; Coe *et.al*., 1995).

Motivated by this concern, the latter studies have focused on estimation of trade effect on foreign investment. To capture the spillover effect from international trade, the researches propose several methods to weight foreign R&D investment. The attempted methods are 1) equal weights with domestic R&D investment (Keller, 1998), 2) weights based on bilateral export shares (Funk, 2001), 3) weights based on inward or outward FDI flows (van Pottelsberghe de la Potterie, 2001)and 4) weights based on the bilateral technological proximity between countries (Park, 1995).

In the same vein, the purpose of this paper is also to propose alternative network methods to weight foreign R&D investments. Although new attempts to estimate the influence of trade have become increasingly sophisticated, the extant model of international R&D spillovers conceptualizes "the global market as an empty box to which a national economy is connected by its overall trade exposure" (Cao, 2010). In other words, the current models consider only the effect of agent-side (nation-state) to the empty-box market. However, the more realistic nature of trade cannot be fully captured by bilateral relations between nation and market, but by a complex system of networks where nations are embedded in and connected by multiple networks (Cao, 2010). Thus, even though the countries have the same amount of import from global market, the impact from trade could be differently imposed to each nation depending on their relative positions in the network. Appling this to technology spillovers, the micro level networks that each nation makes construct the complex forms of global scaled network structure that could constrain or facilitate nations' absorption of technology or the creation of technology.

However, knowledge diffusion mechanism studies at the trade network structural level have not been attempted. Even though some network analysts try to measure the trade network effects, the topics are mainly concentrated on 'isomorphism dynamics' of policies across countries, not directly related to knowledge or innovation. Moreover, Powell, Nooteboom, Gilsing, and many other sociologists have conducted their research on networks, knowledge creation, and absorption, but the unit of their analysis is limited to firms at the national level. Therefore, until now, the link between the studies of network mechanisms of knowledge and trade effect of technology spillovers is absent.

For this reason, this paper will apply diffusion mechanisms of social network analysis to the model of international R&D spillovers. The rest of this paper will be organized as follows. In Section II, the network models for the diffusion mechanism are suggested for more a precise estimation of technology spillovers through trades. This concept has been neglected in previous studies of the productivity function. Section III illustrates the results of panel analysis with a brief description of the data. The implication of the diffusion mechanisms among OECD countries will be discussed in Section IV. Section V presents the supplementary analysis for developing countries and its implication and Section VI concludes the findings on the trade network and technology diffusion.

2.0 THEORETICAL RESOURCES

2.1 The Coe and Helpman Model of International R&D Spillovers

The model of international R&D follows the theoretical underpinning of Arrow (1962): the treatment of knowledge spillovers from capital investment and each unit of capital investment not only increases the stock of physical capital, but also increases the level of the technology for all firms in the economy

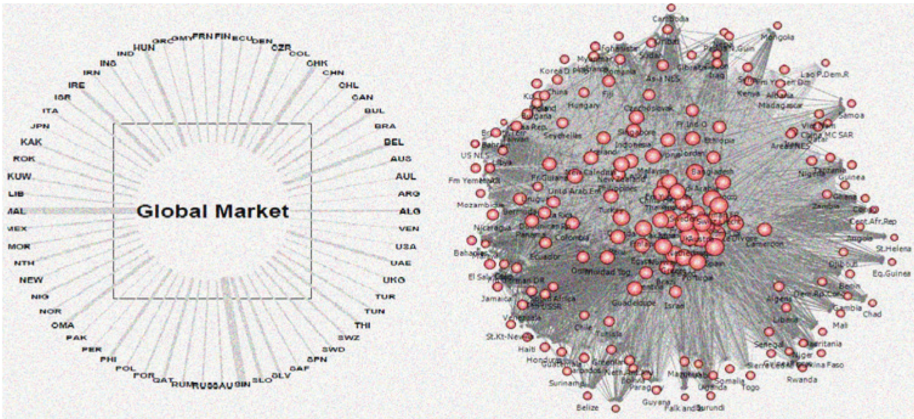

Figure 1: Market as Empty Box vs. Network view of Trade[2]

through knowledge spillovers. Thus, Romer suggested the following equation (Romer, 1986) for spillovers: Y= A (R) F (R_j K_j, L_j), where K_j and L_j represent capital and labor, and R_j stands for the stock of results from expenditures on R&D by Firm j. Romer also assumed that spillovers from R&D improve the public stock of knowledge A.

Grossman and Helpman (1991) specified this model by measuring the total factor productivity (F = Y/ (K_j, L_j)) and applying the equation as a dependent variable. Their empirical specifications are based on two canonic models of endogenous growth: Romer's love of variety approach and the quality ladder theory of Grossman and Helpman (1991) and Aghion and Howitt (1992). In Romer's theory, total factor productivity is raised by the expansion of the range of available inputs; moreover, the investment in the development of new inputs raises the stock of knowledge, which reduces future R&D costs for both domestic and foreign firms by international trade. The theory of the quality ladder illustrates that the quality of an input raises its productivity by a fixed proportional factor; therefore, today's improvement of a product enables future innovators to begin their improvement from a higher quality level. As a result, R&D spillovers occur. These theoretical bases produce the empirical specification created by Coe and Helpman (1995):

$$log\ F_i = a_i^0 + a_i^d\ logS_i^d + a_i^{fm}\ \mathrm{m_i}\ logS_i^f + \varepsilon_i \quad (1)$$

[2] The left figure of a market as an Empty box is Cao, Xun, "Global Network and Domestic Policy Convergence A Network Explanation of Policy Chang" Working Paper, p. 44; The Right figure of the Network view of Trade is from the Author's network analysis

where *i* is a country index, F is a total factor productivity, S^d is the real domestic R&D capital stock, S^f is the real foreign R&D capital stock, *m* is the share of import in GDP, which is included to denote the various impact of foreign R&D with the level of imports by interacting the import share with the foreign R&D capital stock and ε is a well-defined error (Coe *et.al*, 2008). Following to the extended model of Coe and Helpman (1995, 2008), a third specification allows the impact of domestic R&D to differ between the largest seven economies and the others; moreover, a human capital is included due to the new model's lengthier time period and increased heterogeneity of countries compared to the pre-model.

$$log\, F_i = a_i^0 + a_i^d\, logS_i^d + a_i^{dG7}\, G7log_i^d + a_i^h\, log\, h_i^d + a_i^{fm}\, m_i\, logS_i^{f-biw} + \varepsilon_i \quad (2)$$

To compare the foreign R&D weight measurement between that used in Coe and Helpman model and the indictors of network knowledge diffusion mechanisms, the below specifies the calculation process of $logS_i^{f-biw}$, which is defined the bilateral-import-share-weighted foreign R&D capital stock. The specification is,

$$S_i^{f-biw} = \sum_{j\neq i} wij\, S_j^d \quad (3)$$

where $w_{ij} = M_{ij} / \sum_{j\neq i} M_{ij}$, $\sum_{j\neq i} w_{ij} = 1$, and M_{ij} is country i's imports of goods and services from country j based on the bilateral imports.

2.2 Network Mechanism of Knowledge Spillovers in the International Trade

Knowledge Adsorption

Productivity benefits by knowledge are associated with the mechanism of absorbing knowledge and of creating new knowledge. In network organization theory, the capacity of the knowledge adsorption of a certain country can be estimated by the density of connections (direct and indirect) the country possesses. However, the connections, or links, can be interpreted differently by its structural position within the macro network (aggregated construction of each node's networks): if the interaction channels (or communication probability) that the country has are primarily hindered by other nodes' control, the capacity of information adsorption of the country becomes lower than other nodes with the same number of links. Conversely, if the country lies on the path between two nonadjacent nodes, the country potentially has some control over the information flow between the two nonadjacent actors (Wasserman and Faust, 1994). In this position, the capacity of knowledge adsorption is higher than for other nodes with the same amount of links. This method of link estimation is termed 'betweenness centrality' in social network analysis. The index of betweenness centrality forms a network-wide (global) measure and takes direct and indirect ties into account (Gilsing *et.al*, 2008). Thus, this indicates how far an organization can potentially reach all (including distant) parts of the network. The index of betweenness centrality can be specified by the following equations.

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk} \tag{4}$$

The number of geodesics linking is g_{jk}. If all these geodesics are equally likely to be chosen for the path, the probability of the communication using any one of them is simply $1/g_{jk}$. $g_{jk}(n_j)$ stands for the number of geodesics linking the two actors that actor i involves. Under the assumption that geodesics are equally chosen for the path, the probability of actor *i*'s involvement is $g_{jk}(n_j)/g_{jk}$. Therefore, the actor betweenness index for ni is the sum of the probabilities over all pairs of actors without i^{th} actor (Wasserman and Faust, 1994)

The Creation of Knowledge

The increased productivity through knowledge are also related to the creation of novel knowledge as Romer mentioned, "new inputs raises knowledge stock". The critical dispositions for creation knowledge are higher chance of being faced with different kinds of knowledge and information (Burt, 1992). This is not only beneficial for novelty value but also creates a need to understand potentially unrelated information. This is because being a highly central player requires exploration at small technological distances in order to be able to absorb knowledge from all parts of the network. Moreover, success in exploration requires a dual emphasis on the benefits of non-redundant contacts for potential novel combinations as well as on network density for integrating the diverse inputs obtained from such contacts. (Hansen, 1999; McEvily and Zaheer, 1999; Rowley *et.al.*, 2000; Ahuja, 2000). The index of effective sizeis mostly used to estimate this structural position. The specification of the index is given below:

$$\text{Effective size of } i\text{'s network, } E_{ij} = \sum_j [1 - \sum_q p_{iq}\, m_{jq}] \quad q \neq i, j \tag{5}$$

For node i, portion of node i's relationship with node j that is redundant to portion of node i's relationship with other primary contacts, which are also connected to j. Assume that the information node i receives from node j is 1. Redundancy means the amount of information that node i can receive from other nodes. The efficiency is one minus redundancy summed up for all alters. And effective size is the sum across relationships of efficiency in each alter node.

I borrow the insights from network mechanisms of knowledge spillovers and speculate that these network positions can capture more precisely the structural effect of trade networks regarding knowledge spillovers than import share of GDP. More specifically, I expect:

> Hypothesis 1: The more (betweenness) centrally posited in trade networks, the higher level of productivity the country achieves, because the betweenness central position facilitates the absorption of knowledge by reducing others' control on information flow.

> Hypothesis 2: A large effective size in network position that increases the probability of being faced with different kinds of knowledge and information induces the creation of novel knowledge and raises the productivity.

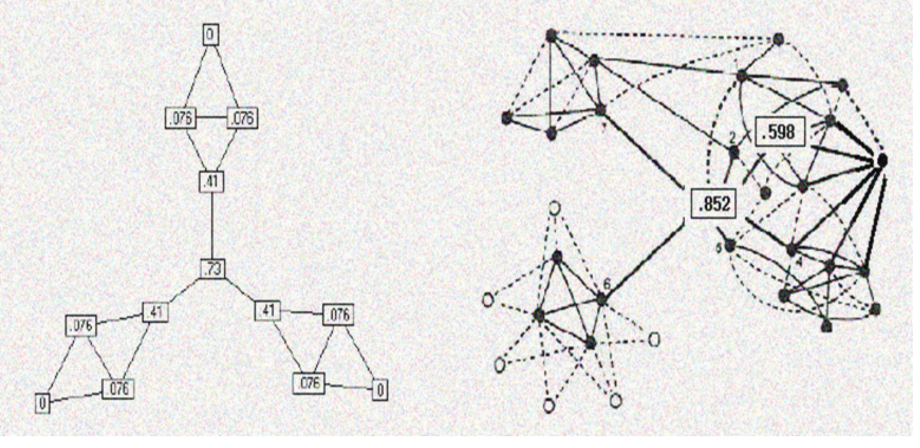

Figure 2: Network Structure of Betweenness Centrality and Effective Size[3]

[3] The numbers of the left figure are measured by the index of betweenness centrality; the numbers of right figure are measured by the index of effective size. These figures show what kinds of nodes can have the network characteristics of betweenness centrality or effective size.

3.0 ANALYSIS MODEL OF NETWORK MECHANISM WEIGHTED FOREIGN R&D CAPITAL

3.1 Data

This paper applies the 2008 dataset of Helpman, Coe and Hoffmaister constructed for the study of international R&D spillovers and institution, since this database covers the widest range of countries and times: twenty-four OECD countries and the period of 1971-2000. In this dataset, the human capital data is also included, which is measured by years of schooling. The data of domestic R&D capital and foreign R&D capital are driven from the OECD Directorate of Science Technology, and Industry. Furthermore, to include the 'total factor productivity' as a dependent variable (Total factor productivity), I adopt the indicator that is made by Coe and Helpman who define it as the log of output minus a weighted average of labor and capital inputs using factor shares as weight, and developed the indicators. Moreover, the import-share of GDP from 1971 to 2000 is also included.

To represent network mechanism for knowledge diffusion effect, I employ total international trade exchange, which are 164 (nations) x 164 (nations) from 1971 to 2000. The data composed of absolute aggregated amount of exchange from exporting countries to receiving countries, which are drawn from

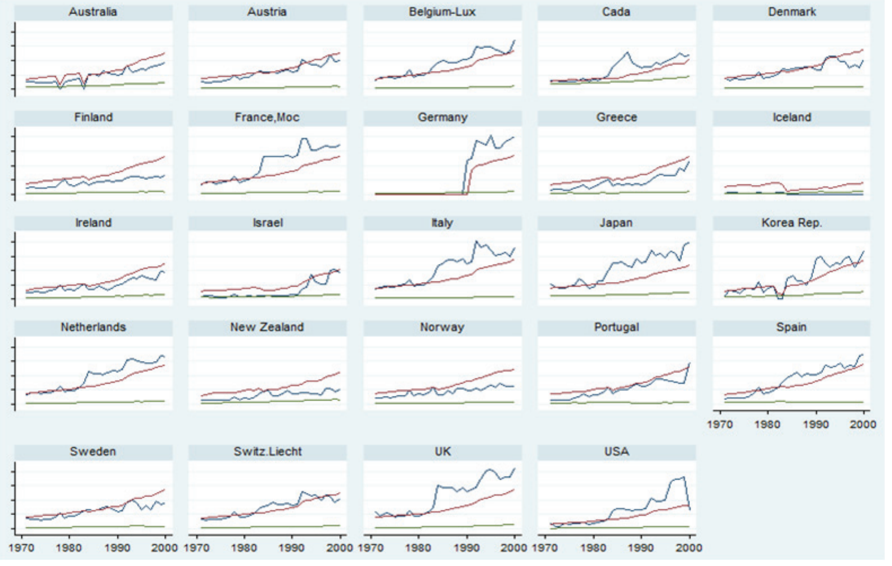

Figure 3: Comparison on $S^{f\text{-}biw}$, $S^{f\text{-}bc}$ and $S^{f\text{-}effs}$ (Green is $S^{b\text{-}biw}$, Blue is $S^{f\text{-}bc}$ and Red is $S^{b\text{-}effs}$)

Table 1: Summary Statistics for OECD countries

Mean (71-00)	Productivity	Domestic Capital	Import share	$S^{f\text{-}biw}$	$S^{f\text{-}bc}$	$S^{f\text{-}effs}$	Human Capital
Australia	0.82	14919	0.17	538476	1863939	2567953	10.12
Austria	0.79	10226	0.34	230399	2409863	2801309	8.04
Belgium	0.82	21509	0.62	227286	3584056	2948272	8.24
Canada	0.85	37734	0.28	1112022	2736309	2079063	10.37
Denmark	0.81	7977	0.34	211008	2668356	3069882	9.51
Finland	0.7	7729	0.28	231700	1701390	2894656	8.58
France	0.82	152576	0.22	252024	4295806	2992010	7.17
Germany	0.83	240147	0.25	215855	2513299	1505837	8.82
Greece	0.91	688	0.26	211920	1683887	2672621	7.01
Iceland	0.8	69	0.36	232967	80737.31	1111602	7.56
Ireland	0.57	1966	0.57	366997	1949112	2662755	7.91
Israel	0.95	8329	0.52	424987	1148939	1967792	8.78
Italy	0.83	62118	0.21	247067	4339982	3059957	5.9
Japan	0.83	352669	0.1	653959	4276596	2750865	8.56
Korea	0.59	24432	0.32	620848	3004404	2579003	8.02
Netherlands	0.85	41382	0.52	280621	3878303	3014972	8.37
New Zealand	0.92	1496	0.29	396800	1264944	2408970	11.17
Norway	0.71	7493	0.36	222453	1774500	2826459	9.52
Portugal	0.75	1501	0.33	230904	2111526	2781871	3.74
Spain	0.91	13853	0.19	329707	3468821	2962800	5.65
Sweden	0.84	29888	0.31	244807	2422880	2969511	9.62
Switzerland	0.95	43730	0.33	249337	2950087	2805041	9.65
UK	0.79	208610	0.27	294142	4603490	2953092	8.51
US	0.9	1373872	0.1	154372	2549225	1657814	11.51
Average	0.81	111038	0.31	340861	2636685	2585171	8.43
Min	0.57	69	0.1	154372	4603490	3069882	3.74
Max	0.95	1373872	0.62	1112022	80737.31	1111602	11.51

IMF's Direction of Trade tables. The tables are basically constructed with dyad relations, however, network structure indicators are calculated by the network-wide (global) relationship between country and country including indirect and non-adjacent countries' potential influence. Summary statistics for the data are presented in Table 1 and the comparison between bilateral-import-share-weighted ($S^{f\text{-}biw}$) for foreign R&D capitaland betweeness centrality($S^{f\text{-}bc}$)/ effective size-weighted ($S^{f\text{-}effs}$) for foreign R&D capital is shown in Figure 3.

In Figure 3, the panel-data line plots illustrate three types of estimation for foreign R&D capital from 1971 to 2000 in 24 OECD countries. As clearly shown in Figure 3, the bilateral import share weights on foreign R&D capital have substantially different trends from the weights measured by betweenness centrality and effective-size. The bilateral import share weights on foreign R&D capital consistently maintain at the lower level in every country, while the two other network estimations show large flucturations over time and across countries, except Iceland. Moreover, the betweenness centrality/effective size weights on foreign R&D investment present the acsending pattern over times in almost all countries. This trend is particularly discernable in Belgium, France, Italy, Japan, Korea, Netherland, Spain and UK, while northern Europe, Norway, Switzland, Sweden and Filand show relatively gradual increase of the two network estimations over time. These observations imply that the two network estimations can capture the dynamic patterns of countries and more detailed changes of the foreign R&D capital, compared to the bilateral import share weights estimation.

3.2 Model

In order to compare the satatisical power of explanation between classic model of international knowledge spillovers using $S_i^{f-b\,iw}$ and the model using indicators of network knowledge diffusion mechanisms, I apply two new estimations of foreign R&D capital capital:

$$S_i^{f-bc} = \sum_{j \neq i} bc_{ij}\, S_j^d \tag{6}$$

$$S_i^{f-effs} = \sum_{j \neq i} effs_{ij}\, S_j^d \tag{7}$$

where $bc_{ij} = C_B(n_i) / (\sum_{j \neq i} C_B(n_i)/N)$ and $C_B(n_i)$ is country i's betweenness centrality (see equation [4]), and in the same vein, where $effs_{ij} = E_{ij} / (\sum_{j \neq i} E_{ij}/N)$ and E_ij is country i's effective size. country i's (see equation [5]). As mentioned above, two network indicators represent the structural nature; I transformed these as fraction of average betweeness centrality or effective size of all nations in the trade (N=164), rather than fraction of the sum of betweenness centrality among the sample countries, 24.

These new estimations for foreign R&D are applied to the Coe and Helpman Model of technology spillovers (equation [2])

$$log\, F_i = a_i^0 + a_i^d\, logS_i^d + a_i^{dG7}\, G7log_i^d + a_i^h\, log h_i^d + a_i^f\, \mathrm{m_i} logS_i^f + \varepsilon_i \tag{8}$$

(Here, $a_i^d \mathrm{m_i} logS_i^f$ will be

$a_i^{f-biw} \mathrm{m_i} logS_i^{f-biw}$ or $a_i^{f-bc} \mathrm{m_i} logS_i^{f-bc} a_i^{f-effs} or$ $\mathrm{m_i} logS_i^{f-effs}$)

4.0 RESULTS

Table 2 illustrates the statistical results of domestic and foreign R&D capital as the long-run determinant of total factor productivity. The first three columns are the results of specifications of Coe and Helpman's model (1-3), and the remaining two are the results of specifications, including network estimation of foreign R&D capital 4 & 5). The estimated coefficients on $\log S^{f\text{-}d}$ decrease substantially in the first two specifications, which are consistent with the results of Coe and Helpman's model (1995). This reduction is largely caused by the inclusion of the human capital variable, which is regarded as one of the determinants of productivity. This is supported by the results that consistently show the highest t-statistics across the model. In contrast, Coe and Helpman's assumption that the impact of domestic R&D differs between the largest seven economies and others is found to be statistically insignificant in all of the models, so that the domestic R&D gap between the G7 and other countries does not affect the change of productivity.

Comparing the results of three different types of foreign R&D estimations, broadly consistent results are obtained; however, slight differences are found in t-statistics and coefficients. A $m\log S^{f\text{-}eff}$ presents the largest t-statistics, and $m\log S^{f\text{-}bc}$ the smallest, but $m\log S^{f\text{-}biw}$ has the largest coefficient and, again, $m\log S^{f\text{-}bc}$ is the smallest. However, from the results, it is still ambiguous which estimation is the most precise measure of foreign R&D capital, due to the trivial gaps among the measures. Overall, though, these estimates confirm that the key elements of Coe and Helpman's

Table 2: Specification in Coe and Helpman Model with Network foreign R&D estimates

(1st line: Coef, 2nd line: Stad.Err, 3rd: Z-Score)

	1	2	3	4	5
$logs^{d}$	0.082	0.041	0.063	0.064	0.068
	(0.005)	(0.006)	(0.06)	(0.006)	(0.006)
	16.18	**6.87**	**10.48**	**10.52**	**11.06**
G7 $logs^{d}$		-0.001	-0.04	-0.005	-0.006
		(0.005)	(0.006)	(0.006)	(0.006)
		-1.79	**-0.71**	**-0.83**	**-1.012**
logh		0.604	0.68	0.663	0.639
		(0.048)	(0.048)	(0.049)	(0.05)
		12.73	**14.13**	**13.54**	**12.93**
$logS^{f\text{-}biw}$	0.223	0.152			
	(0.135)	(0.134)			
	16.49	**11.38**			
$mlogS^{f\text{-}biw}$			0.043		
			(0.005)		
			8.2		
$mlogS^{f\text{-}bc}$				0.037	
				(0.005)	
				8.16	
$mlogS^{f\text{-}effs}$					0.039
					(0.04)
					8.67
R-sq	0.16	0.2	0.17	0.17	0.17
Waldchi2	1535.26	1939.42	1721.59	1658.62	1685.49

theoretical model are, for the most part, statistically significant except G7 $logs^{d}$; moreover, the results of network estimations for foreign R&D prove two hypotheses – betweenness centrality and effective size are positively correlated to the productivity. By showing highly significant estimated coefficients, these results also verify that the network estimations of foreign R&D accurately explain the productivity change of 24 countries from 1971 to 2000.

Table 3 focuses on the specification with three different kinds of foreign R&D capital that interact with import shares of GDP. As shown in the first three columns of Table 3, the three different weight estimations for foreign R&D capital present almost identical results. Despite the absence of G7$logs^{d}$, the general trend of estimated coefficient and t-statistics remains the same: the estimation using effective size has slightly larger t-statistics than any of the others, and the estimation using bilateral-import-share-weighted foreign R&D has the largest coefficient. When $mlogS^{f\text{-}biw}$ and $mlogS^{f\text{-}effs}$ are in the same regression, however, the estimated coefficient of $mlogS^{f\text{-}biw}$ becomes insignificant while that of $mlogS^{f\text{-}effs}$ stays consistently significant. Moreover, in the regression that includes two estimations, the estimated coefficients of other variables remain the same when only effective size-weighted foreign R&D capital is used. Similar results are also generated when $mlogS^{f\text{-}bc}$ and $mlogS^{f\text{-}effs}$ are included in the same regression. The t-statistics of $mlogS^{f\text{-}bc}$ decline sharply from 8.3 to -0.26, which means that the estimated coefficient of $mlogS^{f\text{-}bc}$ is now insignificant; however, although the t-statistics of $mlogS^{f\text{-}effs}$ are also reduced, the estimated coefficient of $mlogS^{f\text{-}effs}$ is still statistically significant at the level of .05. Furthermore, as shown in the earlier example, the coefficients of other variables do not show any change compared to model (4), where only effective size-weighted estimation is applied. However, when the regression includes $mlogS^{f\text{-}biw}$ and $mlogS^{f\text{-}bc}$, neither of the two estimated coefficients remain significant. These results could be understood as reflecting multi-colinearity; however, these results definitely illustrate that the estimation of effective size-weighted foreign R&D capital performs much better than the other two estimations based on bilateral-import-share-weighted or betweenness-size-weighted foreign R&D capital. Although the statistical powers are incomparable between these two estimations, at least we can conclude that each can explain the productivity when used separately.

By applying the above results to network mechanism theories for the absorption and creation of knowledge, we can obtain an important implication. As Romer mentioned (1994), developing countries and developed countries require different sorts of knowledge diffusion mechanisms. For developing countries, it is crucially important to know the mechanisms that facilitate access to the knowledge that already exists in order to improve their productivity. On the other hand, for the developed countries, the mechanisms that stimulate the creation of novel knowledge are substantially important for upgrading their technology. As explained in the hypotheses above, betweenness centrality is the concept of facilitating access to existing knowledge; and effective size represents the position for encouraging the exploration of novel knowledge.

Table 3: Comparison Foreign R&D capital of Coe and Helpman Model with that of Network Knowledge mechanisms

	1	2	3	4	5	6
$Logs^d$	0.062***	0.062***	0.066***	0.066***	0.066***	0.063***
	(0.058)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
logh	0.700***	0.687***	0.666***	0.666***	0.665***	0.688***
	(0.047)	(0.048)	(0.048)	(0.049)	(0.048)	(0.048)
$mlogS^{f\text{-}biw}$	0.042***			0.0006		-0.002
	(0.005)			(0.015)		(0.038)
	8.35			**0.04**		**-0.04**
$mlogS^{f\text{-}bc}$		0.037***			-0.004	0.039
		(0.004)			(0.016)	(0.033)
		8.3			**-0.26**	**1.18**
$mlogS^{f\text{-}effs}$			0.039***	0.038***	0.043***	
			(0.004)	(0.013)	(0.016)	
			8.74	**2.9**	**2.68**	
R-sq	0.18	0.18	0.18	0.18	0.18	0.18
Wald chi2	1875.44	1806.15	1830.89	1839.9	1838.62	1812.64

(p-value *<.05, **<.01, ***<.001)

Therefore, the result that effective-size-weighted foreign R&D estimates most precisely the productivity of OECD developed countries is consistent with the theory of the creation of knowledge network mechanisms. Given that the network mechanisms not only verify the existence of knowledge spillovers, which have been done by many other studies of the technology spillover effects of trade, but also identify the path or network arrangements for the creation of knowledge. Thus, this result could be applied to design trade networks on a national level; in particular, when deciding strategic trade partners and how to organize them for better development of technology.

5.0 SUPPLEMENTARY ANALYSIS

The culmination of the research on technology spillovers and economic growth is achieved when hypotheses are applied to developing countries. However, since Coe and Helpman's research was conducted in the 1970s, the developing countries have not been the subject of technology spillover research. Though the qualitative case studies often dealt with the technology diffusion issues in Asian or African states, the quantitative analysis on the topic has not appeared yet.

The obvious reason is the absence of refined data. The sophisticated indicator of productivity, 'multifactor productivity', which Coe and Helpman have long used to study the technology diffusion among OECD countries, has not been done for the developing countries. The proximate indicator of productivity, such as GDP per employed person, of developing countries sorely exists. Even worse, there are few indicators for human capital, the control variable, that cover developing countries for a long and sustained period of time.

In this research, I conduct supplementary analysis of technology spillovers of developing countries by applying non OECD countries to Coe and Helpman's model. Due to the limited data, the results cannot shed light on the mechanisms underlying technology spillovers among non OECD countries, but the research can show the outlines of the effect of foreign R&D channeled through trade relations on productivity. If the developing countries are left behind, we might not capture even the conventional condition related to technology diffusion among developing countries, which can be found with primitive data.

This supplementary model to explain technology spillovers in developing countries uses the proximate indicators for each variable. To measure productivity, I use the concept of 'labor productivity' defined as GDP per hour worked or employed people (Freeman 2008). In this paper, labor input is the total number of hours worked or total employment and the output is gross domestic product. Thus, I used the data of GDP per employed people as an indicator of productivity. For human capital, which is the control variable in the technology spillovers model, I use life expectancy instead of years of schooling. Human capital consists of labor attributes like knowledge, health and

Table 4: Summary Statistics for Non OECD countries

Mean (1996-2000)	Productivity	R&D Expend'	Import Share	Sf-biw	Sf-bc	Sf-effs	Human Capital
Argentina	24,799	1,200	0.12	9,380	2,940	88,400	73.5
Bolivia	24,799	1,200	0.12	9,380	2,940	88,400	73.5
Bulgaria	11,536	100	0.57	45,400	2,440	81,000	71.2
Chile	28,143	182,000	0.29	17,600	1,620	58,200	76.1
China	4,238	60,800	0.18	13,200	15,140	103,400	70.9
Colombia	15,342	300,000	0.19	9,460	1,275	40,200	70.5
Costa Rica	15,545	11,860	0.46	36,000	10	27,600	77.4
Egypt	10,499	563	0.25	19,600	37	36,600	67.8
Hungary	17,817	72,800	0.62	45,200	3,480	79,200	70.7
India	4,723	123,800	0.13	8,600	6,900	79,200	60.9
Kuwait	14,883	18	0.40	32,750	567	61,250	73.7
Madagascar	1,449	5,825	0.31	26,750	4	30,000	58.0
Malaysia	18,916	1,116	0.95	74,667	6,533	98,333	71.9
Mexico	18,067	14,760	0.32	25,000	4,340	61,000	73.8
Pakistan	7,234	3,750	0.18	14,250	13,750	106,000	62.8
Peru	11,424	166	0.18	15,000	1,500	70,500	69.6
Poland	17,144	3,920	0.29	23,400	6,960	98,000	73.2
Romania	6,168	184	0.35	27,800	3,900	87,000	70.0
Singapore	38,096	2,420	1.62	130,000	7,800	96,800	77.5
Thailand	12,598	8,575	0.48	38,750	10,325	104,750	72.5
Trinidad Tbg	31,257	47	0.48	38,600	2	22,200	68.8
Tunisia	12,660	95	0.42	33,200	1,980	69,400	72.4
Turkey	18,988	351	0.24	19,000	7,460	98,000	68.2
Uruguay	24,269	585	0.20	15,400	11	38,800	74.2
Average	16,275	33,172	0.39	30,349	4,246	71,843	70.8
Max	38,096	300,000	1.62	130,000	15,140	106,000	77.5
Min	1,449	18	0.12	8,600	2	22,200	58.0

skills that produce economic value. Thus, life expectancy could be the indicator of the ability of labor, particularly for developing countries, of which main industry is agriculture. The indicator for R&D expenditure is the same as OECD model. I use the data of the gross domestic expenditure on research and development.

This dataset covers 24 non-OECD countries from 1996 to 2000. The observed countries are evenly distributed; eight from Latin America, six from Asia, six from the Middle East/Africa and four from Eastern Europe. Then, I applied this dataset to the model of Coe and Helpman and tested the effect of network weighted estimation on changes in domestic productivity as well.

The results of supplementary analysis conducted for developing countries are somewhat different from the previous results shown by OECD countries. While the productivity of OECD countries is largely influenced by their own domestic R&D capital, the productivity of non OECD countries is rarely affected by domestic expenditure on R&D. Developing countries' increased rate of productivity, rather, is caused their neighbors' expenditure on R&D.

In terms of the specific indicators for foreign R&D capital's effect on domestic productivity, all the three measures—bilateral import share weight, effective size weight, and betweeness centrality weight— explain the changes in domestic productivity at the statistically significant level, as shown in models 2, 3 and 4 in <Table 5> . However, it is not possible to determine which estimation more precisely measures the technology spillover effect because the R-sq of each indicator shows few differences. Moreover, as model 1 in <Table 5> shows, multicollinearity among these three explanatory variables makes comparison impossible. However, because all foreign R&D measures have statistically significant z-scores, we can infer at least that technology spillovers occur across developing countries.

Table 5: Coe and Helpman's Model Applied to Non OECD Countries and Network Estimator

	1	2	3	4	
logSd	0.02	0.02	0.02	0.02	*coef*
	(0.01)	(0.01)	(0.01)	(0.012)	*(Std.Err)*
Domestic R&D Expenditure	1.36	1.36	1.36	3.95	*Z-score*
logh	2.2***	2.25***	2.25***	2.19***	*coef*
	(0.55)	(0.54)	(0.54)	(0.55)	*(Std.Err)*
Human Capital	4.03	4.19	4.19	3.95	*Z-score*
logSf-biw	-0.22	0.01**			*coef*
	(0.13)	(0.004)			*(Std.Err)*
Import-weighted estimator	-1.75	3.15			*Z-score*
logSf-effs	-0.03		0.12***		*coef*
	(0.03)		(0.004)		*(Std.Err)*
Effective size weighted estimator	-1.03		3.2		*Z-score*
logSf-bc	0.256			0.02**	*coef*
	0.14			(0.01)	*(Std.Err)*
Btw Centrality weighted	1.82			3.07	*Z-score*
R-sq	0.46	0.49	0.48	0.45	
Wald chi2	47.51	46.91	47.32	43.35	

(p-value *<.05, **<.01, ***<.001)

These results reveal that the technology channeled through trade is the main source of endogenous economic growth for developing countries. In other words, the increase of productivity in low-income countries is more sensitive to the increase of their trade partners' R&D expenditure than to their own R&D investment. That is, again, the circumstantial evidence of Romer's statement (1994), '…developing countries… crucially important to …facilitate access to the knowledge that already exists in order to improve their productivity.' Since developing countries' weak infrastructure to produce knowledge and improve technology, the more efficient way to increase their productivity is to imitate their neighbors' advanced technological devices by trade and add values on the existent devices, rather than originally invent new ones. Thus, the results demonstrate that one country's productivity increases more when its trade partners spend more on R&D; moreover, the foreign R&D effect is more essential than domestic R&D expenditure, for developing countries wishing to increase their productivity.

6.0 CONCLUSION

This paper attempts to propose a more sophisticated model that addresses the structural trade mechanisms for technology spillovers. The intangible nature of technology makes it difficult to capture concrete spillover mechanisms, particularly those that accrue at international level. However, the combination of separately developed models, associated with knowledge diffusion from economics and sociology, provide links to identify the mechanisms embedded in complex trade networks. Endogenous growth theorists confirm the factors that determine national and international knowledge spillovers and their relations with econometric models, while social network analysts dissect the complex flow of knowledge exchange and discover the main structural network mechanisms for the absorption and creation of knowledge.

Thus, this paper connects two separate models by applying network estimations representing knowledge diffusion to the Coe and Helpman model of international R&D spillovers. The results of panel analysis from 1971 to 2000 on 24 OECD countries validate that both network estimations can explain productivity as much as, or more than, classic measurements. For instance, the network estimator of effective size performs much better than Coe and Helpman's estimation - the bilateral-import-share-weighted for foreign R&D capital. This result implies not only the validity of the network estimators, but more importantly, it provides the structural network positions in which nations benefit relatively more for creating new knowledge. Therefore, these findings offer developed countries policy implications that help how to decide trade partners and organize them for effective absorption or creation of knowledge.

In addition, I applied the same model to 24 non OECD countries. Though for developing countries the sophisticated indicators like multifactor productivity or human capital have not yet developed, I deduced the conventional facts using proximate measurements. Although the results cannot determine which estimators—network or bilateral import share—have more explanatory power, the results reveal that the trade partners' R&D expenditure have more crucial effect on the productivity of developing countries, than on their domestic capital for R&D.

This is an initial step that examines the structural network mechanism for technology spillovers. For further improvement, it is necessary to gather a larger sample of countries and long period of time. The lack of data on the R&D expenditure of developing countries, human capital and multifactor productivity is the main hindrance to extending the implications of this study, given the fact that technology could work to break the poverty trap for developing countries that lack natural resources and the network mechanism research might provide the policy implications. The collection of data or the creation of alternative models should be pursued to fully take advantage of international technology spillovers.

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