DISCUSSION PAPERS IN ECONOMICS

Working Paper No. 05-06

An Explanation of OECD Factor Trade with Knowledge Capital and the HOV Model

Shuichiro Nishioka
University of Colorado at Boulder

October, 2005

Revised: October, 2006

Center for Economic Analysis
Department of Economics

University of Colorado at Boulder
Boulder, Colorado 80309

An Explanation of OECD Factor Trade with Knowledge Capital and the HOV Model

Shuichiro Nishioka*
University of Colorado at Boulder

October 2006

Abstract

This study examines the international factor trade of the developed (OECD) countries within the Heckscher-Ohlin-Vanek (HOV) model. Previous empirical work largely has not supported the HOV predictions for OECD trade, perhaps because of the similarity in factor abundance among those countries. In this paper a previously unexplored factor -- knowledge capital (measured by cumulative R&D stock) -- is introduced into the HOV framework. Knowledge capital likely plays an important role in determining comparative advantage among OECD countries because they specialize in high-tech products and also show dissimilarity in knowledge abundance. By using a new dataset for fifteen OECD countries, I find strong support for the strict HOV model with the addition of knowledge capital. Moreover, the introduction of knowledge spillovers further improves performance of the HOV model.

F11: Neoclassical Model of Trade
O33: Technological Change; Choices and Consequences; Diffusion Processes
Keywords: Heckscher–Ohlin; Trade, International Transfer of Technology

---

* Department of Economics, 256 UCB Boulder CO USA 80309-0256, Tel: (303) 579-6542,
E-mail: snishioka@colorado.edu. I particularly thank Keith E. Maskus, Martin Boileau, John T. Cuddington, Wolfgang Keller, and James R. Markusen for their guidance and support throughout this project. All errors are mine.

1. Introduction

In recent decades the developed members of the Organization for Economic Cooperation and Development (OECD) have converged in such economic measures as GDP per capita and capital abundance. According to the standard Heckscher-Ohlin-Vanek (HOV) model, the growing similarity in relative factor abundance should lead to a decrease in within-group international trade relative to trade between the OECD and other countries. However, OECD trade has grown annually by five percent over the last 10 years and trade among these countries still captures around 70 percent of the global volume (the World Development Indicators[1]).

In spite of its intuitively appealing theoretical predictions, the HOV model has performed poorly in empirical studies, at least in a strict form (e.g., Maskus 1985; Bowen, Leamer, and Sveikauskas 1987; Trefler 1995). As suggested by Maskus (1985) and Leamer and Levinsohn (1995), the assumptions of the HOV model are too restrictive to hold in practical data analysis. Subsequently, many economists have tried to identify which assumptions account for the empirical failures. Trefler (1995) found support for the HOV model when allowing Hicks-neutral productivity differences along with home-country bias. Davis and Weinstein (2001) obtained empirical support when country-specific technologies were used to compute factor contents of traded goods under a modified version of factor-price equivalence. Considering bilateral factor trade, Debaere (2003) showed that a relative HOV model holds well for country-pairs involving one developed ("North") and one developing ("South") country, but not for North-North country-pairs. This result is intuitive for in North-South pairs, capital-labor ratios are different whereas in North-North pairs they are similar. Therefore, Debaere's results seem to imply that the HOV model is incapable of explaining OECD factor trade.

[1] The World Bank (2006)

In the last twenty years, theories based on increasing returns to scale (IRS) and differentiated products (e.g., Helpman and Krugman 1985) have been invoked to explain bilateral trade among OECD countries, in the belief that the HOV model cannot account for the large volume of such trade. Evenett and Keller (2002) analyzed the gravity equation to find the extent to which the two workhorse theories, IRS and Heckscher-Ohlin, are responsible for the empirical success of the gravity equation. They found that increasing returns better explain the volume of North-North bilateral trade and that factor-abundance explains the volume of North-South trade. Thus, their results were consistent with Debaere's claim that the factor abundance (HOV) model is inappropriate to explain OECD trade.

The point of departure of the current study is conceptually similar to the contributions by Dollar (1993) and Davis (1997). Dollar argued that knowledge capital (R&D stock) was potentially a major source of comparative advantage among developed countries. Institutions that generate new knowledge and technology from ongoing R&D activities can be a source of comparative advantage, particularly for high-technology industries. These advantages may persist for important periods of time, even if technological information diffuses fully in the long run. Davis (1997) introduced systematic technology differences in a model involving North-type and South-type products, along with North-type and South-type factors, to show that a large volume of North-North trade is possible in the HOV model.

The present article builds on these ideas by focusing on OECD countries where North-type goods are produced with North-type factors. In particular, knowledge capital is introduced as a separate factor input of these products, recognizing that OECD countries specialize in high-technology products that require R&D activities. Knowledge capital is more distinctive than other factors in terms of differences in factor abundance among OECD countries. Just five nations (France, Germany, Japan, the United Kingdom, and the United States) account for 88 percent of total OECD knowledge, with the U.S. share being 45 percent.[2]

The literature on productivity and the creation of ideas is founded on knowledge as an input (e.g., Grilliches 1986, Romer 1986, and Adams 1990). Yet there is little treatment of knowledge capital in the context of the factor-abundance model. An exception is Ekholm (1998), who applied the knowledge capital model of multinational enterprises (Carr, Markusen, and Maskus 2001) to the revealed factor abundance model. This model assumes that services of knowledge-based and knowledge-generating activities, such as R&D, advertising, and management, can be geographically separated from production and supplied at low cost to multiple production facilities. Using data for the United States, Ekholm showed that omission of intra-firm knowledge transfers leads to biased measures of revealed factor abundance.

Rather than considering direct transfers of knowledge, the present study rests on the HOV foundation and treats knowledge as an immobile factor, with products embodying knowledge capital. Knowledge capital is defined as the discounted sum of R&D expenditures within each country and represents a stock of newly developed ideas permitting the introduction of new products and higher-quality goods. For example, the cutlery of Solingen, Germany is famous for its quality, design, and level of details. The product embodies not only centuries of craftsmanship but also recent efforts to update product quality. Even though both Germany and Vietnam produce cutlery, the quality of their products differs and the former are knowledge-intensive compared with the latter.

I construct a comprehensive dataset of 15 OECD countries. These data show considerable support for business knowledge capital as a separate, and fundamentally important,

[2] These figures are set out in Table 3 below. The share of these five countries for physical capital (labor) is 77 percent (80 percent).

factor in the HOV model. For 11 countries the HOV theoretical prediction is confirmed: knowledge-abundant countries have net-exports of knowledge capital. In addition, there is little evidence that knowledge capital demonstrates what Trefler (1995) called "missing trade." In contrast, other factors in the dataset (physical capital and aggregate labor) show missing trade.

Recognizing that knowledge is partially non-excludable and non-rival, and therefore not fully immobile, I account for the possibility of international knowledge spillovers (e.g., Branstetter 2001; Keller 2002; and Peri 2005). My estimation of knowledge spillovers is based on geography and technology. Spillovers between countries are negatively related to geographic or technological distance. Allowing for knowledge diffusion in the current study improves the sign fits and narrows the gap between measured and predicted factor contents of trade for most countries. Finally, the results of the HOV model are further improved by introducing country-specific measures of capital and labor productivities. I estimate these productivities from each country's technologies according to the framework in Maskus and Nishioka (2006) and find that these productivities are positively and significantly correlated with country-level knowledge intensities.

The remainder of this paper is organized into three sections. In Section 2, I define knowledge capital by providing a detailed discussion of its economic properties and introduce four types of that factor, depending on assumptions about spillovers. In Section 3, I develop and test the strict HOV models with knowledge capital. In addition, various productivities are introduced to adjust international differences in factor efficiency. Finally, I present concluding remarks in the last section.

2. Knowledge Capital

To characterize knowledge capital as an economic factor, I discuss the essential properties of knowledge (Romer 1990 and Grossman and Helpman 1991). Goods and factors are characterized by their degree of rivalry and excludability. The purely rival good has the property that its use by one agent precludes its use by another. The good is excludable if the owner of the good can prevent others from using it. Conventional economic factors such as physical capital and labor strictly entail both rivalry and excludability. These properties do not apply as clearly to knowledge capital. Privately invented knowledge might entail properties similar to public goods at least in the long run, and be partially non-excludable and non-rivalrous.[3]

Partial non-excludability reflects the difficulty owners of knowledge face in preventing others from making unauthorized use of it. Particularly in developed countries, this problem is addressed legally through intellectual property rights, which prevent unauthorized use without contractual compensation. Still, both unauthorized use and compensated use ultimately would diffuse the knowledge; such capital cannot be perfectly excludable.

This property suggests that R&D may generate technology spillovers. Branstetter (2001) found strong evidence for intra-national spillovers but not international spillovers with firm-level data of Japan and the United States. Keller (2002) used data for OECD countries and found that geographical location plays an important role in technology diffusion. Assuming the five largest countries are the sources of business R&D stocks for nine other OECD countries, Keller showed that technology spillovers are strongly related to geographic distance.

Thus, the literature implies that knowledge spillovers are far more local than global. This is the key insight supporting my treatment of knowledge as, at least partially, an internationally immobile factor. The other property of knowledge, non-rivalry, is important to the extent that

[3] Romer (1990) discusses issues related to knowledge as economic goods and provides examples.

multinational firms choose to transfer it to foreign affiliates. In this paper I do not pursue knowledge spillovers related to multinational firms, focusing instead on the geographic localization found by Keller (2002) and Peri (2005).

2A. Measuring Knowledge Capital

I first develop baseline knowledge capital stocks from the OECD STAN R&D database (2004). Real business R&D expenditures are employed and I apply the perpetual-inventory method to obtain business knowledge capital (S1):

$$S^B_{cit} = (1-\delta)S^B_{cit-1} + R^B_{cit} \qquad (1)$$

where S^B_{cit} is the business knowledge capital (S1) for country c, industry i, and time t, δ is the depreciation rate of knowledge obsolescence, and R^B_{cit} is the real business R&D expenditure adjusted by a country level deflator of non-residential total business investment. To obtain the initial value (1987) of R&D stock, I compute:

$$S^B_{ci1} = R^B_{ci1}/(0.1+\delta+g^B_{ci}) \qquad (2)$$

where $g^B{}_{ci}$ is the average growth rate of sectoral real business R&D expenditures for industry i and country c over the period between 1987 and 2001. For the depreciation rate Grilliches (1986) and Adams (1999) used 0.15, whereas Keller (2000) used 0.05 and Keller (2002) employed 0.10. I use the intermediate value of 0.10, which means that knowledge capital depreciates relatively slower than physical capital, to which I apply the standard depreciation rate of 0.1333.

The next specification includes both business and public knowledge capital. Public R&D consists of government and higher-education expenditures. These expenditures are derived from the OECD Main Science and Technology Indicators (2005). This specification is important because the HOV model focuses on national-level factor endowments, which might include public R&D as well.[4] The definition of national knowledge capital (S2) follows:

$$S_{cit}^{N} = (1-\delta)S_{cit-1}^{N} + R_{cit}^{B}[(R_{ct}^{B} + R_{ct}^{P}) / R_{ct}^{B}] \tag{3}$$

where S_{cit}^{N} is national knowledge capital, R_{ct}^{P} is total public R&D expenditure (volume) for country *c* and time *t*, and $R_{ct}^{B} = \Sigma_i R_{cit}^{B}$. To allocate public knowledge to individual sectors, I make the identifying assumption that it spreads within the country according to the business R&D share. In this case, the initial value follows:

$$S_{ci1}^{N} = R_{ci1}^{B}[(R_{c1}^{B} + R_{c1}^{P}) / R_{c1}^{B}]/(0.1 + \delta + g_{ci}^{B}) \tag{4}$$

Finally, knowledge capital stocks with spillovers are introduced, where such spillovers add to the knowledge of recipient countries without diminishing that of the source countries. The strategy to estimate the amount of international knowledge spillovers is based on Keller (2002), who assumed that sectoral production functions relied on Dixit and Stiglitz-type input differentiation and trade is subject to iceberg transport costs. The former assumption implies that the level of sectoral total factor productivity (TFP) must be positively related to the amount of knowledge capital, while the latter means that productivity depends as well on spillovers from foreign countries. One important deviation from Keller is that I do not limit the flows of knowledge from the largest five to other OECD countries. Instead I permit spillovers to arise both among the five largest nations and among the others as well. That is, all the OECD countries are potential sources and recipients of bilateral spillovers. In addition, I control the amount of spillovers (capacity to absorb foreign knowledge) by the size of recipient industries.

As noted above, business knowledge capital accumulates disproportionately across countries. This is also true across industries, as shown in Appendix Table A-2. Most of the

[4] This specification is similar to Griliches (1986) who discussed the plausibility of including public R&D expenditure in knowledge capital.

industrial business knowledge is concentrated in four industries: chemicals (18.2 percent), electrical equipment (37.2 percent), motor vehicles (13.1 percent) and other transportation (14.6 percent). Therefore, it is important to control not only cross-country but also cross-industry size of business knowledge.

I first calculate the multilateral TFP index of Caves, Christensen, and Diewert (1982).[5] The multilateral "superlative" TFP index is defined as: $\ln TFP_{cit}=(\ln V_{cit}-(1/C)\Sigma_c \ln Y_{cit})-\sigma_{cit}(\ln L_{cit}-(1/C)\Sigma_c \ln L_{cit})-(1-\sigma_{cit})(\ln K_{cit}-(1/C)\Sigma_c \ln K_{cit})$ where C is the number of countries in the dataset, V_{cit} is real value added for country c, industry i, and time t, L_{cit} is labor (adjusted by working hours), K_{cit} is physical capital (fitted values), and σ_{cit} is the fitted values of the labor-compensation share (labor compensation over value added). These figures are displayed in Figure 1 for each country. Then I estimate the following equations with non-linear least squares:

$$\ln TFP_{cit} = d_{ci} + d_t + \alpha \ln[S^B_{cit} + \beta L_{cit}(\sum_{h \neq c} S^B_{hit} e^{-\gamma D^{ch}})] + \varepsilon_{cit} \tag{5}$$

$$\ln TFP_{cit} = d_{ci} + d_t + \alpha \ln[S^B_{cit} + \beta L_{cit}(\sum_{h \neq c} S^B_{hit} e^{-\varphi TD^{ch}_{it}})] + \varepsilon_{cit} \tag{6}$$

where D^{ch} is the geographic distance[6] between country c and h, and TD^{ch} is the technology distance between country c and h.[7]

Equation (5) is the pure "distance" specification. The parameter α represents the elasticity of TFP with respect to overall business knowledge (including spillovers) and βL_{cit}

---

[5] I use the adjusted values for capital, labor, and labor-compensation share [e.g., Harrigan (1997); Keller (2002)]. The dataset consists of 15 countries and 13 manufacturing industries from 1987 to 2001 (I exclude sectors 7 "Refined Petroleum Products" and 17 "Other Manufacturing" because they contain sub-sectors of different characters). Finally, because relatively reliable industrial deflators are available for these 13 industries of 15 countries, I use the industrial GDP deflators to obtain real value added, real knowledge capital, and real physical capital.

[6] The distance, in thousands of kilometers, between two countries' capitals, as used by Robertson (1998) and available at http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeData.html#Gravity

[7] I do not include spillovers of public knowledge because public knowledge is characterized as basic research. Technology distance is defined as the difference between per capita knowledge of a knowledge recipient country and a knowledge sender:

$$TD^{ch}_{it} = \left| S^B_{hit} / L_{hit} - S^B_{cit} / L_{hit} \right|$$

determines the strength of the distance-weighted foreign knowledge effect on TFP growth. As the industry size of the home country (L_{cit}) gets larger, the amount of the spillovers diffused from foreign industries also grows. Ideally, the capacity to absorb foreign knowledge depends on the number of R&D researchers. However, those data are not available for most of the industries. Therefore, sectoral employment levels are used as a proxy for R&D researchers. In equation (5), geographical distance is the only factor to impede international spillovers. On the other hand, equation (6) represents the "technology" specification where technological distance impedes spillovers, as in Peri (2005). The idea is that spillovers exist mainly between industries within the same technological groups. For instance, it is difficult for technology followers (Ethiopia) understand and absorb advanced knowledge from technology leaders (the United State).

As shown in Table 1, in these TFP equations all signs are as expected and statistically significant. In addition, compared with the no-spillover models (S1 and S2), the elasticities of TFP with respect to overall knowledge (α) are higher: 0.176 for the distance equation and 0.189 for the technology specification.

Using the estimated coefficients from these equations, I develop the following empirical definitions of augmented knowledge capital: (1) S_{cit}^{GS} denoted as business knowledge capital with "geographic" spillovers from (S3); and (2) S_{cit}^{TS} denoted as business knowledge capital with "technology" spillovers (S4):

$$S_{cit}^{GS} = S_{cit}^{B} + \beta L_{cit} (\textstyle\sum_{h \neq c} S_{hit}^{B} e^{-\gamma D^{ch}}) \tag{7}$$

$$S_{cit}^{TS} = S_{cit}^{B} + \beta L_{cit} (\textstyle\sum_{h \neq c} S_{hit}^{B} e^{-\varphi TD_{it}^{ch}}) \tag{8}$$

Table 2 provides summary statistics of the four knowledge specifications in 1997. There are fifteen OECD countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United

States. These countries together accounted for approximately 75 percent of world GDP in 1997 and a larger share of global business and public R&D. For business knowledge, the G5 countries (United States, United Kingdom, France, Germany, and Japan) generated 88 percent of total knowledge capital in the 15-country sample, with the U.S. share close to half, at 44.5 percent. Interestingly, the business R&D-scarce countries perform relatively larger amounts of public R&D. For example, in Australia the public R&D stock was 120 percent of the business R&D stock, with analogous figures for Spain (95 percent) and Italy (80 percent). For this reason the share of the United States decreases to 42 percent when the public R&D stock is included.

Spillovers from business knowledge stocks had strong impacts on the non-G5 OECD countries. While those countries found their knowledge increased from foreign sources by around 50 percent of domestic stocks, the large G5 countries had it rise by around 20 percent. For instance, Canada and the Netherlands absorbed large amount of foreign knowledge from geographic spillovers, with total spillovers being 101 percent of domestic knowledge for Canada and 71 percent for the Netherlands. These countries are located close to leading knowledge producers, respectively the United States and Germany.

2B. Knowledge Capital as an Input of Production

Following Romer (1986) and Adams (1990), I formulate the production function to include knowledge capital among the factor inputs. To show the plausibility of treating it as an input in a CRS production function, a foundation of the HOV model, I estimate production functions with the various types of knowledge capital defined above.[8] Model 1 is the most flexible, placing no restrictions on returns to scale, estimated with business knowledge capital

[8] Estimation strategies are discussed in Appendix B. I note here that output is defined as value added because I have no comparable data on intermediate inputs.

(S1). Models 2 through 5 employ CRS technology with the different type of knowledge capitals (S1-S4, respectively). Finally, Model 6 posits a CRS technology without knowledge capital.

Estimation results with robust standard errors are in Table 3.[9] In Model 1 the coefficients on knowledge capital are positive and statistically significant for nine of 13 industries, but negative coefficients for textiles (-0.02) and motor vehicles (-0.01) and statistically insignificant *t*-statistics for paper products (0.69) and rubber and plastics (0.91). When the assumption of constant return to scale is imposed (Models 2 through5), the number of negative coefficients declines. In particular, all coefficients on business knowledge become positive (Model 2). The coefficients on knowledge capital are reasonable for a production function (around 0.09 for other transportation and around 0.15 for chemicals and electrical equipment) and less than those on physical capital and aggregate labor.

To test the restriction on constant returns to scale when knowledge capital is included, I study the coefficients on the log of employment. These coefficients must be zero if industries exhibit constant returns to scale and positive under increasing returns to scale. A perhaps surprising result is that there is no statistically significant evidence of increasing returns except in motor vehicles, food products, and paper products. Four industries demonstrate statistically significant decreasing returns to scale.[10] Although the Schwarz Information Criteria (SIC)[11] indicate that the Model 1 (no constraint on returns to scale with knowledge capital included) is the best specification among the six models, the CRS models with various definitions of

[9] The results are similar when I employ feasible generalized least squares (FGLS).
[10] Harrigan (1999) derived similar results with data for 11 OECD countries. This pattern of results may be partially explained by the fact that most of the variation in industry size is across countries, particularly between the G5 group and the non-G5 group. This suggests that the G5 countries may have disproportionately large industries with moderate economies of scale, but that unrestricted estimation cannot distinguish between country fixed effects and scale economies. Another reason for the decreasing returns to scale may be related to the estimation with value added (not gross output) with no consideration of intermediate goods (e.g., Jorgenson, Kuroda, and Nishimizu 1987).
[11] Let l be the value of the log of the likelihood function with the k parameters estimated using T observations: $SIC=-2(l/T)+k\log(T)/T$

knowledge capital (Models 2 through 5) outperform the CRS model without knowledge capital (Model 6). Thus, with respect to CRS production functions the inclusion of knowledge capital seems to be an appropriate extension of standard production theory.

3. Knowledge Capital in the HOV Model

Assume that all countries have identical CRS production functions with three factors: physical capital, knowledge capital, and aggregate labor. Markets for goods and factors are perfectly competitive. There are no barriers to trade or transport costs in goods but factors are immobile across borders. I also assume that the distributions of factors are consistent with integrated equilibrium so that factor prices are equalized across countries.

I begin the derivation of the strict HOV model with the identity equation of the net export vector for country *c*. The sectoral net-export vector (of dimension N) is the difference between the net production vector and the final consumption vector:

$$T_c = (I - B_c)Q_c - C_c \tag{9}$$

where T_c is an N×1 vector of net exports, Q_c is an N×1 vector of gross output, and C_c is an N×1 vector of final consumption. B_c is an N×N input-output (indirect) matrix of the unit intermediate requirements so that $(I\text{-}B_c)Q_c$ equals the net output vector Y_c. The direct technology matrix for country *c*, A_c, is of dimension F×N (F factors and N industrial sectors) and its elements (a_{cif}) represent the amount of a factor (*f*) needed for one unit[12] of gross output (Q_c) in each sector *i*.

Pre-multiplying equation (9) by direct and indirect technology matrix $A_c(I\text{-}B_c)^{-1}$ and applying the factor exhaustion assumption $A_cQ_c=V_c$ where V_c is an F×1 vector of factor endowments for country *c*, yields the standard equation that a country's net factor contents of

[12] The unit of output is price adjusted million 1997 PPP basis U.S. dollars.

trade is the difference between factors absorbed in production (V_c) and factors absorbed in final consumption ($A_c(I\text{-}B_c)^{-1}C_c$):

$$A_c(I-B_c)^{-1}T_c = V_c - A_c(I-B_c)^{-1}C_c \tag{10}$$

Assume identical and homothetic preferences (IHP) along with identical prices of goods and services so that each country consumes final goods in the same proportion. Final consumption can be expressed as a proportion of world net output (Y_w):

$$C_c = s_c Y_W \tag{11}$$

where s_c is the expenditure share for each country in total world expenditure. Because the production technology is identical worldwide, the U.S. technology is chosen to derive the following strict HOV equation:

$$F_c = V_c - s_c V_W \tag{12}$$

where V_w represents the F×1 vector of world factor endowments (the sum of fifteen OECD countries in the dataset), $F_c=A_{US}(I\text{-}B_{US})^{-1}T_c$ is the measured factor contents of trade, and $V_c\text{-}s_cV_W$ is the predicted factor contents of trade. Thus, the HOV model tells us that measured factor contents of trade for any country must equal the difference between the country's factor endowments and the product of national consumption shares and world factor endowments. This is the strict HOV prediction identified by Leamer (1980).

To check the performance of this model, standard testing procedures have been developed (Maskus 1985; Bowen, Leamer, and Sveikauskas 1987; Trefler 1995; Davis and Weinstein 2001). First, a sign test obtains the probability of sign coincidences between measured and predicted factor contents of trade. If the HOV model held perfectly, the sign coincidence would be 100 percent. However, the sign fit usually has been close to 50 percent, which means the probability of sign coincidence is no better than a coin toss. Next, a slope test involves regressing measured factor contents of trade on predicted factor contents of trade without a constant. If the HOV model held, the regression coefficient (and coefficient of determination) would be unity. HOV generally has failed this test as well. Finally, variance ratios across countries are developed for each factor, computing the variance of measured factor contents of trade over the variance of predicted factor contents of trade. Under HOV the ratio should be unity but previous literature has shown that this number tends to be close to zero, reflecting Trefler's (1995) missing trade. I use these three criteria to discuss the performance of the HOV model with knowledge capital included.

Because it is difficult to estimate aggregate world data, I introduce the modified version of the HOV model proposed by Staiger, Deardorff and Stern (1987) and Hakura (2001) that can test the HOV model using country pairs without the need for world aggregates. In this *pair-wise* model, under the strict HOV assumptions, two countries are chosen [for example Germany (c=1) and Japan (c=2)] and the ratio of equations (11) for these two countries becomes:

$$C_1 = (s_1 / s_2)C_2 = s_{12}C_2 \tag{13}$$

where $s_{12}=s_1/s_2=C_1/C_2$.

Again assume identical direct and indirect technologies. Using equation (13) and equation (12) for both countries, the pair-wise HOV model follows:

$$F_1 - s_{12}F_2 = V_1 - s_{12}V_2 \tag{14}$$

where F_1-$s_{12}F_2$ is the measured *relative* factor contents of trade and V_1- $s_{12}V_2$ is the predicted *relative* factor content of trade. Because I have fifteen countries, there are 105 country-pairs for each factor. I apply the sign test, slope test, and variance test to equation (14).

3A. Overview of the Dataset

My dataset of 15 OECD countries and 23 industries consists of four elements. First are factor endowments, including physical capital (K_{cit}), aggregate labor (L_{cit}), and various measures of knowledge capital (S_{cit}) from 1987 to 2001. Second are country-specific technologies, involving three-factor direct technology matrices (A_{ct}) from 1987 to 2001 and indirect (intermediate usage) technology matrices (B_c) for 1997. Third are production data, incorporating real gross output (Q_{cit}) and real value added (Y_{cit}) from 1987 to 2001. Finally are figures on net output (Y_{ci}), net-exports (T_{ci}), and final consumption (C_{ci}) for 1997, which come from each country's input-output structures.[13] The dataset is similar to that of Hakura (1999) who developed a 23-sector dataset of four European countries with seven factors (including various skill groups), and to that of Davis and Weinstein (2001) who constructed a 35-sector dataset of 10 OECD countries with two factors. As in other studies of this kind, sectoral aggregation of the dataset might cause statistical bias.[14] Further, in my data sectoral labor cannot be disaggregated into various skills. Nonetheless, the dataset covers most of the economic activities of the world.

3B. Results of Testing the HOV Model with Knowledge Capital

In Table 4, I present the initial test results, beginning with physical capital and aggregate labor. Here, equation (12) is designated the HOV model and equation (14) the pair-wise HOV model. As may be seen, both physical capital and aggregate labor perform poorly. Although the proportions of sign fits are strictly better than a coin toss for physical capital in both specifications, the slope tests and variance ratios indicate serious missing trade. For example, the HOV model achieves slightly positive slopes but the variance ratios are essentially zero for

---

[13] See Appendix A for detailed discussion of data development and manipulation.
[14] Aggregation may cause systematic bias for factor contents of trade as discussed in Feenstra and Hanson (2000). See Hakura (1999) as well.

both factors. The variance ratios improve under the pair-wise HOV model but the slope coefficient of aggregate labor is estimated to be negative, a clear rejection of the HOV reasoning.

This poor performance of conventional factors confirms the basic result of previous literature involving the strict HOV model (Bowen, Leamer, and Sveikauskas 1987; Trefler 1995; Davis and Weinstein 2001; and Hakura 2001). Additional results indicate that the United States is estimated to be an importer of both physical capital and aggregate labor, which is confirmed by the predicted factor contents of trade.[15] This tendency is consistent with Trefler's (1993) data but differs from Bowen, Leamer, and Sveikauskas (1987), who found that United States imported aggregate labor services but exported physical capital services in 1966.

Compared with physical capital and aggregate labor, however, knowledge capital performs impressively. As shown in Table 4, in the case of business knowledge capital, the HOV model predicts 73 percent sign fits and the pair-wise HOV model predicts 81 percent sign fits. Further, there is far less evidence for missing trade, as the variance ratios rise to 0.34 for both HOV and pair-wise HOV. These results improve still further if public knowledge is introduced. The sign fit of HOV improves to 80 percent (twelve of fifteen countries). Moreover, the variance ratio rises to 0.41. This tendency also holds for the pair-wise HOV model, which obtains 83 percent sign fits and a variance ratio of 0.43.

Figure 2-1 depicts the statistical relationship between predicted and measured business knowledge capital contents of trade for all countries in the sample. Japan, Germany, France, and Sweden are estimated to be the main net exporters of knowledge, which is confirmed by the predicted knowledge contents of trade. On the other hand, Australia, Canada, and the United Kingdom are the main importers of knowledge. The technology matrix of the United States

[15] In the pair-wise model the United States is estimated as an importer of physical capital vis-à-vis 12 countries (all except Japan, Spain, and the United Kingdom) and of labor vis-à-vis 10 countries (all except Australia, Belgium, France, Italy, and Spain).

indicates that there exists heterogeneity in the sectoral unit requirements of knowledge capital. Other vehicles (including airplanes), electrical equipment (including semiconductors), chemicals (including pharmaceuticals), and motor vehicles are the four most knowledge-intensive sectors. It is likely that the strong predictive performance of knowledge capital in the HOV model reflects the influence of these sectors through trade. Japan and Germany are two major producers and exporters of motor vehicles, France is one of two main producers of commercial airplanes, Australia and Canada are importers of electrical equipment, and the United Kingdom is an importer of motor vehicles.

Before examining the results with knowledge spillovers, I discuss the interpretation of diffused knowledge in the context of the HOV model and whether it should be included in the world aggregate knowledge stock. For instance, if knowledge invented by France could spillover to Belgium, there are two possibilities for computing world (two-country) knowledge: (1) simply count the knowledge invented by France and Belgium; (2) count both the original French and Belgium stock but add to it the knowledge diffused to Belgium. In the latter case, the amount of two-country aggregated knowledge would be greater than the former. Considering knowledge as an input for production, double-counting of French knowledge diffused to Belgium is appropriate because Belgium needs French knowledge as an input to produce high-quality goods. Therefore, I count diffused knowledge as part of the world aggregate knowledge stock.

The results with knowledge spillovers are given in Table 4. With the standard HOV model, the sign fit of business knowledge improves to 80 percent with geographic spillovers and to 93 percent with technology spillovers. The statistical relationships are in Figure 2-2 (the case of technology spillovers), demonstrating an even tighter regression fit. Business knowledge capital contents for Belgium, Denmark and the United States achieve the correct sign concordances after technology spillovers are taken into account. Thus, incorporating diffused knowledge stocks estimated from geographic and technological distances improves sign fits and narrows the gap between measured and predicted factor contents of trade for most countries.

However, the amount of geographic spillover is disproportionately low for countries located far from Europe and North America. In particular, Australia and Japan receive little foreign knowledge, amounting to less than 1 percent of domestic knowledge. As a result, the sign fit of the pair-wise HOV model deteriorates to 76 percent by 5 percent. Another important result is that the United States becomes an importer of knowledge capital in terms of both predicted and measured factor contents of trade after spillovers are introduced. Overall, the improved fit of HOV and pair-wise HOV with knowledge stocks suggests that knowledge is an important element to explain international trade between OECD countries.

3C. Indirect Effects of Knowledge on Factor Productivities

Prior literature has demonstrated the importance of productivity adjustments in improving the performance of the standard HOV model (e.g., Trefler 1993, 1995; Harrigan 1997, 1999; Gabaix 1997; Maskus and Nishioka 2006). Two types of productivity adjustments have been introduced: (1) differences in Hicks-neutral TFP (e.g., Trefler 1995; Davis and Weinstein 2001; Harrigan 1997); and (2) factor-specific productivity differences (e.g., Trefler 1993; Maskus and Nishioka 2006). I next implement these ideas into the three-factor production structure. Note that international differences in productivities presumably depend on research, making knowledge capital itself an underlying determinant of technical variations across countries. Not only this idea is introduced as factor-specific productivities but also I remain within the standard framework in which each factor, including knowledge capital, is affected by unmodeled determinants as Hicks-neutral TFP.

Hicks-neutral differences in total factor productivities (normalized by U.S. levels) were already estimated in Table 3 for Models 2-5, using the Cobb-Douglas CRS production function:

$$Y_{cit} = M_c M_i e^{\lambda_i t} K_{cit}^{\alpha_{1i}} S_{cit}^{\alpha_{2i}} L_{cit}^{1-\alpha_{1i}-\alpha_{2i}} \tag{15}$$

where M_c represents country-specific TFP.

These Hicks-neutral productivities may be used to derive the efficiency-equivalent units of factors:

$$Y_{cit} = M_i e^{\lambda_i t} (M_c K_{cit})^{\alpha_{1i}} (M_c S_{cit})^{\alpha_{2i}} (M_c L_{cit})^{1-\alpha_{1i}-\alpha_{2i}} \tag{16}$$

where M_cK_{cit} is the TFP-equivalent physical capital in sector *i*, M_cS_{cit} is the TFP-equivalent knowledge capital, and M_cL_{cit} is the TFP-equivalent aggregate labor. Instead of the unadjusted factor inputs I use these TFP-adjusted factors to test the strict HOV and the pair-wise HOV models.

Regarding specific factor-augmenting productivities, Antweiler and Trefler (2002) employed factor prices as proxy measures. However, other literature has estimated them directly from basic datasets (e.g., Trefler 1993; Maskus and Nishioka 2006).[16] I employ the methodology introduced by Maskus and Nishioka (2006) who estimated factor productivities from the unit factor requirements across industries under the assumption of constant returns to scale production technology.

Specifically, let π_{cf} be defined as a productivity parameter with the interpretation that if V_{cf} is the factor endowment of country *c* then $V^*_{cf} = \pi_{cf}V_{cf}$ is the corresponding factor endowment

[16] Gabaix (1997) argued that because the inferred productivities in Trefler (1993) were not calibrated from the factor contents of trade, that article offered no empirical justification for the HOV model with factor-productivity modification. Further discussion is in Maskus and Nishioka (2006).

measured in productivity-equivalent units. Let w_{cf} be the price per units of V_{cf} and let w^*_{cf} be the price per unit of V^*_{cf}. Since one unit of V_{cf} provides π_{cf} productivity-equivalent units of service, $1/\pi_{cf}$ units of V_{cf} provide one productivity-equivalent unit service priced at $w^*_{cf} = w_{cf}/\pi_{cf}$. Assuming identical international technologies at the factor-efficiency level and normalizing productivities of the United States to unity, the HOV model with productivity adjustment for factor f is as follows:

$$F_{cf} = \pi_{cf} V_{cf} - s_c \sum_{g=1}^{G} \pi_{gf} V_{gf} \tag{17}$$

$$w_{cf} / \pi_{cf} = w_{USf} / \pi_{USf} \Leftrightarrow w_{cf} / \pi_{cf} = w_{USf} / 1 \Leftrightarrow w_{cf} / w_{USf} = \pi_{cf} \tag{18}$$

where $\pi_{USf} = 1$, and g indexes the fifteen OECD countries in the data set. This framework is the same as Trefler's (1993) model, in which the HOV model was adjusted by factor-productivities. Implementing it requires estimating factor-productivities (π_{cf}), for which I follow the method of Maskus and Nishioka (2006):

$$a'_{USift} = \pi_{cft} a'_{cift} + \varepsilon_{cift} \tag{19}$$

where a'_{cift} represents unit factor requirement (direct and indirect) for country c, industry i, time t, and factor f. The a'_{cift} variables are developed from the direct technology matrix (A_{ct}) annually from 1987 to 2001 and the indirect technology matrix (B_c) for 1997. By using the dataset of 15 countries and 22 industries (excluding sector 1, which is agriculture. See Appendix A for detail), I estimate factor-specific productivities for all countries from 1987 to 2001 (π_{ctf}) that are estimated with the seemingly unrelated regression (SUR).

These factor-productivities, denoted as π_{cft}, are estimated for physical capital (f=K) and labor (f=L) from 1987 to 2001, imposing the normalization of 1997 U.S. productivities. As is well known, introduction of factor-productivities will improve the fit of the HOV model regardless of the introduction of knowledge capital. Therefore, instead of using the factor productivities (π_{cft}) directly, I first estimate regressions of these productivities on knowledge intensities (knowledge capital per unit of labor or knowledge capital per dollar of physical capital). Then, the fitted values of factor productivities ($\hat{\pi}_{cft}$) are applied to the standard HOV models. As discussed in Maskus and Nishioka (2006), capital productivity is weakly correlated with labor intensity and labor productivity is also weakly correlated with capital intensity. Thus, these sectoral intensities are also included in the set of explanatory variables. Specifically, factor-productivities (labor and capital) are estimated as follows, with country fixed effects (h_c), time fixed effects (h_t), and factor intensities:

$$\pi_{cKt} = h_{cK} + h_{Kt} + \sigma_{1K}(S_{ct} / K_{ct}) + \sigma_{2K}(L_{ct} / K_{ct}) + \varepsilon_{cKt} \tag{20}$$

$$\pi_{cLt} = h_{cL} + h_{Lt} + \sigma_{1L}(S_{ct} / L_{ct}) + \sigma_{2L}(K_{ct} / L_{ct}) + \varepsilon_{cLt} \tag{21}$$

where π_{cKt} (π_{cLt}) represents capital (labor) productivities for country c at time t.

The results of two knowledge-stock specifications (business knowledge (S1) and technology spillovers (S4)) are presented in Table 5. Equations (20) and (21) perform well except that capital intensity (capital/labor) is an insignificant determinant of labor productivity. Importantly, however, knowledge intensities are positive and statistically significant for both productivities. This result provides basic evidence that international differences in factor productivity are partially explained by cumulative research activities and spillovers.

The results of the HOV tests with TFP and factor-productivity adjustments are presented in Table 6. With the TFP adjustments there are no significant improvements from the strict HOV model. Although the sign fits and variance ratios for physical capital improve for pair-wise HOV, the other two factors deteriorate. As in previous literature (Trefler 1995; Davis and Weinstein 2001), Hicks-neutral productivities alone cannot improve the performance of the HOV model. On the other hand, the fitted values of factor productivities perform well, with overall sign fits of all four cases now over 75 percent. In particular, knowledge capital with technology spillovers improves to 82 percent and there is no evidence of missing trade. Combining the fact that knowledge capital fits the HOV model well and knowledge intensities can account for international differences in factor-productivities to a great extent, it seems that knowledge (R&D stock) is an important determinant of comparative advantage among OECD countries.

4. Conclusion

In spite of its theoretical importance, much previous empirical research failed to support the HOV model. The consensus is that similarity in both factor abundance and technologies underlie the empirical failures of the HOV model. However, as has been argued theoretically and conceptually, knowledge capital is a potentially important determinant of comparative advantage. This study offers the first empirical evidence in the HOV framework that knowledge capital plays a crucial role in explaining trade among OECD countries.

By using the dataset of 15 OECD countries, I show strong support for the HOV model augmented by factor productivity differences. My result is different from previous contributions to the HOV literature because the majority of those studies required major modifications in theoretical assumptions. Even though results vary slightly across knowledge-capital specifications, I obtain correct sign fits for 14 of 15 countries using business knowledge and technology-based spillovers. Both the sign fits and variance ratios indicate the strong performance of the HOV model with knowledge capital. Interestingly, knowledge-intensity is strongly correlated with the cross-country variations in factor-productivities. This correlation serves as evidence that knowledge capital improves the performance of HOV for physical capital and aggregate labor in an indirect way. Finally, my findings revive the HOV model as a useful explanation for OECD trade, as conceptualized by Dollar (1993) and Davis (1997), by shedding light on the unexplored factor input of knowledge capital.

In the cases of knowledge spillovers, I borrow ideas from Keller (2002) and Peri (2005) that geographical and technology distances between countries impede knowledge diffusion. For both cases I obtain improvements in sign fits. However, the strength of knowledge spillovers is different based on the spillover specifications. For example, while Australia absorbs 102 percent of domestic knowledge stock when technology-distance based spillovers are introduced, it does not receive any foreign knowledge when geographical spillovers are introduced. Future research could focus on the issue of how to estimate the precise channels and amounts of spillovers. Both geographic features and knowledge transfers from headquarters to their plants could be taken into account. In addition, spillovers might be strongly related to time, with the strength of spillover increasing over longer periods.

References

[1] Adams, James D. (1990) "Fundamental Stocks of Knowledge and Productivity Growth," *Journal of Political Economy* Vol.98, No.4, pp673-702

[2] Adams, James D. (1999) "The Structure of Firm R&D, the Factor Intensity of Production, and Skill Bias," *The Review of Economics and Statistics* Vol.81, No.3, pp499-510

[3] Antweiler, Werner. and Trefler, Daniel. (2002) "Increasing Returns and All That: A View from Trade," *American Economic Review* Vol.92, pp93-119

[4] Bowen, Harry. Leamer, Edward. and Sveikauskas, Leo. (1987) "Multicountry, Multifactor Tests of the Factor Abundance Theory," *American Economic Review*, Vol.77, pp791-809

[5] Branstetter, Lee. (2001) "Are Knowledge Spillovers International or Intranational in Scope?" *Journal of International Economics* Vol.53 pp53–79

[6] Carr, David. Markusen, James R. and Maskus, Keith E. (2001) "Estimating the Knowledge-Capital Model of the Multinational Enterprise," *American Economic Review* Vol.91, pp693-708

[7] Caves, Douglas W. Christensen, Laurits R. and Diewert, W Erwin. (1982) "Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers," *Economic Journal* Vol.92, pp73-86

[8] Conway, Patrick. (2002) "The Case of the Missing Trade and Other Mysteries: Comment" *American Economic Review* Vol.92, pp394-404

[9] Davis, Donald R. (1997) "Critical Evidence on Comparative Advantage? North-North Trade in a Multilateral World," *Journal of Political Economy*, Vol.105, No.5, pp1051-1060

[10] Davis, Donald. and Weinstein, David. (2001) "An Account of Global Factor Trade," *American Economic Review*, Vol.91, pp1423-1453

[11] Debaere, Peter. (2003) “Relative Factor Abundance and Trade,” *Journal of Political Economy* Vol.111, No.3, pp589-610

[12] Dollar, David. (1993) “Technological Differences as a Source of Comparative Advantage,” *American Economic Review* Vol.83, pp431-435

[13] Ekholm, Karolina. (1998) “Headquarter Services and Revealed Factor Abundance,” *Review of International Economics* Vol.6 (4), pp545-553

[14] Evenett, Simon. and Keller, Wolfgang. (2002) “On Theories Explaining the Success of the Gravity Equation,” *Journal of Political Economy* Vol.110, No.2, pp281-316

[15] Feenstra, Robert. and Hanson, Gordon. (2000) “Aggregation Bias in the Factor Content of Trade: Evidence from U.S. Manufacturing,” *American Economic Review* Vol.90, pp155-60

[16] Gabaix, Xavier. (1997) “The Factor Content of Trade: A Rejection of the Heckscher-Ohlin-Leontief Hypothesis,” Harvard University, Department of Economics

[17] Grilliches, Zvi. (1986) “Productivity, R&D, and Basic Research at the Firm level in the 1970’s,” *American Economic Review* Vol.76, pp141-154

[18] Grossman, Gene M, and Helpman, Elhanan. (1991) “Innovation and Growth in the Global Economy,” (Cambridge, MA, The MIT Press)

[19] Hakura, Dalia. (1999) “A Test of the General Validity of the Heckscher-Ohlin Theorem for Trade in the European Community,” *IMF working paper* 9970

[20] Hakura, Dalia. (2001) “Why Does HOV Fail? The Role of Technological Differences within the EC,” *Journal of International Economics* 54, pp361–82

[21] Harrigan, James. (1997) “Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model,” *American Economic Review* Vol.87, pp475-494

[22] Harrigan, James. (1999) "Estimation of Cross-Country Differences in Industry Production Functions," *Journal of International Economics* 47, pp267–294

[23] Helpman, Elhanan. and Krugman, Paul R. (1985) "Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and International Economy," (Cambridge, MA, The MIT Press)

[24] Heston, Alan. Summers, Robert. and Aten, Bettina. (2006) "Penn World Table Version 6.2," (Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania)

[25] Jorgenson Dale M, Kuroda, Masahiro. and Nishimizu, Mieko. (1987) "Japan-U.S. Industry-Level Productivity Comparisons, 1960-1979," *Journal of the Japanese and International Economics* 1, pp1-30

[26] Keller, Wolfgang. (2000) "Do Trade Patterns and Technology Flows Affect Productivity Growth?" *World Bank Economic Review* Vol.14, pp.17-47

[27] Keller, Wolfgang. (2002) "Geographic Localization of International Technology Diffusion," *American Economic Review* Vol.92, pp120-142

[28] Leamer, Edward. (1980) "The Leontief Paradox, Reconsidered," *Journal of Political Economy* Vol. 88, No.3, pp495-503

[29] Leamer, Edward. (1984) "Sources of International Comparative Advantage, Theory and Evidence," (Cambridge, MA, The MIT Press)

[30] Leamer, Edward. and Levinsohn, James. (1995) "International Trade Theory: The Evidence," (Handbook of international economics. Volume 3)

[31] Leontief, Wassily. (1953) "Domestic Production and Foreign Trade: The American Capital Position Re-examined," *Proceedings of the American Philosophical Society* 97, pp332-49

[32] Maskus, Keith E (1985) "A Test of the Hechscher-Ohlin-Vanek Theorem: The Leontief Commonplace," *Journal of International Economics* 19, pp201-212

[33] Maskus, Keith E. and Nishioka, Shuichiro. (2006) "Development-Related Biases in Factor Productivities and the HOV Model of Trade," University of Colorado, Department of Economics

[34] Peri, Giovanni. (2005) "Determinants of Knowledge Flows and Their Effect on Innovation," *Review of Economics and Statistics* 87, pp308-322

[35] Romer, Paul M. (1986) "Increasing Returns and Long-Run Growth," *Journal of Political Economy* Vol.94, No.5, pp1002-1037

[36] Romer, Paul M. (1990) "Endogenous Technological Change," *Journal of Political Economy* Vol.98, No.5, ppS71-S102

[37] Staiger, Robert M. Deardorff, Alan V. and Stern, Robert M. (1987) "An Evaluation of Factor Endowments and Protection as Determinants of Japanese and American Foreign Trade," *Canadian Journal of Economics* Vol.20, No.3, pp449-463

[38] Trefler, Daniel. (1993) "International Factor Price Differences: Leontief was right!" *Journal of Political Economy*, Vol.101, No.6, pp961-987

[39] Trefler, Daniel. (1995) "The case of the Missing Trade and Other Mysteries," *American Economic Review*, Vol.85, pp1029-1046

[40] Trefler, Daniel. (2002) "The case of the Missing Trade and Other Mysteries: Reply," *American Economic Review*, Vol.92, pp405-410

Appendix A: Data Development

I develop the dataset of value added (volume), gross output (volume), labor, physical capital (volume), and business knowledge capital (volume) for 15 OECD countries (Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States) and 23 industries [see Table A-1] from 1987 to 2001. In addition, corresponding 23-sector Input-Output tables (total use) for these countries are developed for the year 1997. The data of exports, imports, final consumptions, net output, and intermediate usages are derived from the I-O tables.

Table A-1: Sectorsof Industrial Activities

sectors	Branches of Activities	ISIC Rev.3
1	Agriculture	01-05
2	Mining and Quarrying	10-14
3	Food Products	15-16
4	Textiles	17-19
5	Wood Products	20
6	Paper Products	21-22
7	Refined Petroleum Products	23
8	Chemicals	24
9	Rubber and Plastics	25
10	Non-Metallic Products	26
11	Basic Metals	27
12	Fabricated Metals	28
13	Machinery	29
14	Electrical Equipment	30-33
15	Motor Vehicles	34
16	Other Transportation	35
17	Other Manufacturing	36-37
18	Electricity	40-41
19	Construction	45
20	Wholesale and Retail Trade	50-55
21	Transport, Strage and Communication	60-64
22	Finance, Insurance and Real Estate	65-74
23	Community Ssocial and Personal Services	75-99

1) Input-Output Data

Input-Output tables (total use) for Australia (1994-1995), Canada (1997), Denmark (1997), Finland (1995), France (1995), Germany (1995), Japan (1997), the Netherlands (1997), Norway (1997), the United Kingdom (1998), and the United States (1997) are from the OECD I-

O database (2002). Belgium (1995), Italy (1995), Spain (1995), and Sweden (1995) are from the Statistical Office of the European Communities (Eurostat). The I-O tables from the OECD I-O database employ ISIC Rev.3 classification containing 41 industrial groups and the I-O tables from the Eurostat employ NACE/CLIO classification containing 59 groups. These two different classifications are aggregated into 23 industrial groups of ISIC Rev.3. The number of industrial groups is smaller than the 35 sectors used by Davis and Weinstein (2001) but is the same as Hakura (2001). Not only the Input-Output matrices but also final consumption, gross output, and net exports are derived from the I-O tables for 1997. Final consumption is a sum of final consumption of households, final consumption and investment of government, gross fixed capital formation, and changes in inventory.[17] Therefore, the total use table of country *c* always satisfies the equation: $T_c=(I-B_c)Q_c-C_c$ where B_c is a 23×23 indirect technology matrix for the unit intermediate requirements so that $(I-B_c)Q_c$ vector equals the net output (Y_c). B_c is obtained by taking input-output data from the I-O tables and dividing inputs in each sector by the corresponding sector's gross output.[18] To convert the dataset into U.S. dollars, purchasing power parities (1997) from the Penn World Table version 6.2 (Heston, Summers and Aten) and the OECD Economic Outlook (2006) are used. Conway (2002) and Trefler (2002) discuss the choice between purchasing power parity (PPP) and nominal exchange rates. For Australia, Belgium, Finland, France, Germany, Italy, Sweden, Spain, and the United Kingdom, the nominal values in I-O tables are uniformly multiplied by the growth rates of the total nominal GDP to adjust the differences from the year 1997.

[17] For Finland, I add discrepancies into final consumption in order to maintain the consistency of the I-O table.

[18] In case of two sectors, the input usage matrix can be obtained as following.

$$B_C=\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}=\begin{bmatrix} x_{11}/Q_1 & x_{12}/Q_2 \\ x_{21}/Q_1 & x_{22}/Q_2 \end{bmatrix} \quad B_C Q_C=\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix}=\begin{bmatrix} x_{11}/Q_1 & x_{12}/Q_2 \\ x_{21}/Q_1 & x_{22}/Q_2 \end{bmatrix}\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix}=\begin{bmatrix} x_{11}+x_{12} \\ x_{21}+x_{22} \end{bmatrix}$$

2) Factor Endowment Data

(A) Physical Capital Stock

Capital stock is developed by the perpetual inventory method (Keller 1999). Gross fixed capital formation values (GFCF) are derived from the OECD structural analysis (STAN) database (2004) and unreported data are estimated from the ISIC Rev.2 version of the OECD STAN database (1995, 1997, and 1998) and Eurostat. As many GFCF data as possible are derived from these databases but there are still some unavailable data. The following procedure is taken to interpolate these data: (1) detailed sectors [(sector 15) "Motor vehicle" and (sector 16) "Other vehicles"] are unavailable but their sub-totals ["Transportation equipments" = (sector 15)+(sector 16)] are available for certain years. In this case, I use the share of the nearest year to allocate the sub-totals to each detailed sector.[19] (2) If the sub-totals are also unavailable, I use the average growth rates of the nearest four years to interpolate the unreported data.[20] One major problem of using GFCF data from the OECD STAN database (2004) is that some countries include residential-investments but other countries do not include them. In particular, "agriculture" (sector 1) and "real estate" in "finance, insurance, and real estate" (sector 22) are the main sources of errors from residential investments. To avoid serious errors, I first deflate nominal values of the real estate sector's GFCF to 35 percent[21] for countries in the dataset except Canada, Japan, the United Kingdom, and the United States. Total non-residential GFCFs are separately obtained from the OECD National Account Statistics (2006) and I allocate the total to

[19] Australia: all manufacturing sectors from 1991 to 2001 (I use the share of available four years only for Australia), Belgium: sectors 15 and 16 from 1987 to 1998, Canada: sectors 15 and 16 from 2000 to 2001, Denmark: (1) sectors 7, 8, and 9 from 1991 to 1992, (2) sectors 11 and 12 from 1995 to 2001, (3) sectors 15 and 16 from 1992 to 2001, France: sector 5 from 1998 to 2001, sectors 11 and 12 from 1997 to 2001, Norway: sectors 7 and 8 from 1996 to 2001, Spain: sectors 11 and 12 from 1996 to 2001, sectors 15 and 16 from 1993 to 2001, and Sweden: sectors 13 and 14 from 1987 to 1989, sectors 15 and 16 from 1987 to 1989.

[20] Denmark: sectors 1-2, 17-23 from 1987 to 1992.

[21] Based on Japanese value.

each sector according to the shares developed from the OECD STAN database.[22] Unfortunately, I cannot adjust "agriculture" (sector 1). Therefore, special attentions must be made when the data from sector 1 is related to the analysis. To convert the GFCFs into real series, the deflators for business investment (non-residential) from the OECD Economic Outlook (2006) are used. After converting into a real local currency series, I develop real capital stock with a depreciation rate of 0.1333 (see; Leamer 1984; Bowen, Leamer, and Sveilauskas 1987; and Davis and Weinstein 2001). Then, the real capital stock is converted into 1997 U.S. dollars by purchasing power parities. For Japan, sectoral GFCF data are unavailable from the OECD STAN database (2004). Therefore, total GFCF series are derived from the OECD National Accounts Statistics (2006) and sectoral shares are obtained from the nominal investment matrix tables of the ESRI-Histat database.[23]

(B) Labor

Sectoral labor inputs (total employments) are derived from the OECD STAN databases (1998 and 2004), the Eurostat, and the OECD Employment by Activities and Status (2006). To interpolate unreported data, I use the available share of the nearest year to allocate the sub-totals to each detailed sector.[24] Country-level average working hours from the OECD Employment and Labor Market Statistics (2006) are used to adjust the international difference in average working hours with the normalization of U.S. working hours.

[22] I use the dataset developed from the OECD STAN database directly for Belgium. In case of Norway, to separate "housing investment" from "other constructions," I use the corresponding shares from Finland and Sweden.
[23] ESRI-Histat database is developed with SNA 68 basis [OECD STAN (rev.3) is based on SNA93]. Thus, computer-software is treated not as investment but as intermediate goods. In addition, to use the sectoral shares from ESRI-Histat, I exclude "construction (housing)" investments.
[24] Australia: sectors 5-9, 13-16 from 2000 to 2001, sectors 11 and 12 from 1998 to 2001, Belgium: sectors 13-16 from 1987 to 1994, Norway: sectors 7 and 8 from 1996 to 2001, and the United Kingdom: sectors 11 and 12 from 1997 and 2001, sectors 15 and 16 from 1995 to 2001.

(C) Knowledge Capital

The data on business R&D expenditure are obtained from the OECD STAN R&D database (1998 and 2004), the OECD Science and Technology Statistics "Table 13" (2006), and the Eurostat. Total business R&D expenditures for sectors 3 to 23 are mainly from the OECD STAN R&D database and those for sectors 1 and 2 are from the OECD Science and Technology Statistics. Government and higher education expenditures on R&D, used to develop national knowledge capital, are from the OECD Main Science and Technology Indicators (2005). The following procedure is taken to interpolate unreported data: (1) if detailed sectors are unavailable but their sub-totals are available for certain years, the shares of the nearest year are used to allocate the sub-totals to each detailed sector.[25] (2) If the sub-totals are also unavailable, the average growth rates of the nearest four years are used to interpolate the unavailable data. If all the sectoral values from 1987 to 2001 are absent, such as for sectors 1 and 2 of the United States, the shares of the corresponding sector's business R&D expenditures for other countries (G4 countries in the case of the U.S. sectors 1 and 2) are used to fill these data. In particular, the following equation is used for the sector 1 of the U.S.: $R^B_{US,1,t}=R^B_{US,t}(1/4)\Sigma_{G4}(R^B_{G4,1,t}/R^B_{G4,t})$ where i=1 is sector 1 ("agriculture"), $R^B_{US,1,t}$ represents business R&D expenditure on agriculture for the United States at time t, $R^B_{G4,1,t}$ is business R&D expenditure of sector 1 for G-4 countries, $R^B_{US,t}$ is total business R&D expenditure of the United States, and $R^B_{G4,t}$ is the total business R&D expenditure of G4 countries. This method is used for Australia (sector 1), Italy (sectors 1 and 2), and the United States (sectors 1 and 2). To convert all the data into a real series, the deflators for business investment (non-residential) from the OECD Economic Outlook (2006) are used. After converting all the R&D expenditures into a real local currency series, I develop real

[25] Belgium: sector 14 from 1987 to 1991, Denmark: sector 15 from 1987 to 1998.

R&D stock with a depreciation rate of 0.10. Then, the real R&D stock is converted into 1997 U.S. dollars by using purchasing power parities.

3) Value Added and Gross Output (Production)

Value added (nominal), value added (volume), and gross output (nominal) series are obtained from the OECD STAN database (1995, 1997, 1998, and 2004) and the Eurostat. The number of unreported data items is much smaller (less than one percent) than that of business R&D expenditures and GFCFs. Most of the unreported data are filled in with interpolation and with the corresponding growth rates of sub-totals. Some unreported data of gross output are filled in with the growth rates of nominal value added. The sectoral-level deflators are developed from nominal and real value added series. By using these 23-sector deflators, the index for gross output (volume) is developed. I choose 1997 as the base year of both value added (volume) and gross output (volume). In the case of base year data of gross output (volume), the values from the I-O tables are employed. All the series are converted into 1997 U.S. dollars by purchasing power parities.

Table A-2. Details of Dataset (year 1987-2001, 15 countries, and 13 manufacturing industries: 1997 PPP $US)

Countries	Value Added (GDP)		Physical Capital		Labor (adjusted employment)		Business R&D stock	
	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)
Australia	2.11	1.47	1.37	1.50	-0.62	1.88	11.66	0.55
Belgium	2.77	1.20	4.17	1.49	-1.25	0.95	7.04	0.99
Canada	3.16	3.46	2.06	2.86	0.21	3.25	10.73	1.52
Denmark	1.51	0.53	-0.43	0.60	-0.98	0.60	11.67	0.30
Finland	4.84	0.68	-1.18	0.78	-1.04	0.71	11.49	0.49
France	2.57	6.26	1.99	5.82	-1.50	5.42	7.14	6.52
Germany	1.19	10.98	0.98	10.10	-2.09	11.35	5.49	11.64
Italy	1.89	6.84	2.57	8.62	-0.39	7.54	3.75	2.87
Japan	2.30	18.42	5.00	27.65	-2.01	22.57	8.56	21.68
Netherlands	2.56	1.55	-1.07	1.60	-0.78	1.24	4.37	1.32
Norway	0.51	0.37	-1.44	0.37	-1.43	0.41	4.33	0.25
Spain	2.72	3.31	2.56	4.36	1.13	4.31	9.83	0.81
Sweden	4.13	1.12	2.29	1.23	-1.01	1.09	10.38	1.48
UK	1.43	6.73	2.39	5.32	-2.02	7.18	7.53	4.81
US	3.72	37.08	5.94	27.70	-0.50	31.51	5.70	44.75
Industries	Value Added (GDP)		Physical Capital		Labor (adjusted employment)		Business R&D stock	
	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)	Growth (%)	Share (%,1997)
Food Products	1.07	12.00	2.41	10.98	-0.33	12.57	7.31	1.97
Textiles	-1.55	5.12	-0.16	4.48	-4.25	9.71	6.70	0.59
Wood Products	0.46	2.23	1.97	2.11	-0.87	3.36	6.71	0.17
Paper Products	1.82	11.65	2.59	11.07	-0.36	11.44	12.68	1.10
Chemicals	2.62	10.83	4.32	11.65	-1.09	5.52	8.17	18.20
Rubber and Plastics	3.22	4.18	3.86	3.70	0.46	4.37	9.58	1.69
Non-Metallic Products	1.76	4.06	2.71	4.13	-1.00	4.14	4.24	1.20
Basic Metals	1.26	4.92	0.82	6.96	-2.47	3.93	3.57	2.12
Fabricated Metals	1.61	8.42	4.35	5.74	-0.15	10.28	7.18	1.38
Machinery	1.17	9.79	5.39	9.53	-0.80	10.35	8.86	6.68
Electrical Equipment	10.35	15.11	5.68	16.22	-1.44	13.94	7.69	37.20
Motor Vehicles	2.44	8.56	4.98	10.63	-0.14	7.36	9.15	13.13
Other Transportation	-0.30	3.11	3.39	2.81	-2.40	3.04	0.41	14.57

Notes: (1) Physical capitals are developed from non-residential gross fixed capital formations (GFCF) from 1987 to 2001.
(2) The year 1997 is the base year of deflators (knowledge capital and physical capital are deflated by country-level non-residential business investment deflators and value added is deflated by industry-level GDP deflators)
(3) Growth rates are averages per year between 1987 and 2001.

Appendix B: Estimations of Production Functions

First, the standard Cobb-Douglas production function with three inputs is assumed:

$$Y_{cit} = M_{ci} e^{\lambda_i t} K_{cit}^{\alpha_{1i}} S_{cit}^{\alpha_{2i}} L_{cit}^{\alpha_{3i}} \tag{B1}$$

where Y_{cit} is value added for country c, industry i and time t, M_{ci} is country-industry specific TFP, K_{cit} is physical capital, L_{cit} is aggregate labor, and S_{cit} is knowledge capital. Also assume that $M_{ci} = M_c M_i$: TFP can be decomposed into industry- and country-specific contributions. From equation (B1), Model 1 follows:

$$\ln(Y_{cit} / L_{cit}) = m_c + m_i + \lambda_i t + \alpha_{1i} \ln(K_{cit} / L_{cit}) + \alpha_{2i} \ln(S_{cit} / L_{cit}) + \beta_{1i} \ln(L_{cit}) + \varepsilon_{cit} \tag{B2}$$

where $m_c = ln(M_C)$, $m_i = ln(M_i)$, $\beta_{1i} = \alpha_{1i} + \alpha_{2i} + \alpha_{3i} - 1$ and β_{1i} is a convenient measure of the extent to which the industry production function differs from constant returns to scale. This equation is the same as equation (12) in Harrigan (1999), except that knowledge capital is introduced here.

Starting from the baseline equation (B2), the constant returns to scale assumption (β_{1i}=0) is imposed:

$$\ln(Y_{cit} / L_{cit}) = m_c + m_i + \lambda_i t + \alpha_{1i} \ln(K_{cit} / L_{cit}) + \alpha_{2i} \ln(S_{cit} / L_{cit}) + \varepsilon_{cit} \tag{B3}$$

This production function is consistent with the HOV model with knowledge capital. Model 2 is equation (B3) with business knowledge (S1), Model 3 with national knowledge (S2), Model 4 with geographic spillovers (S3), and Model 5 is with technology spillovers (S4).

Finally, knowledge capital stocks are excluded from inputs: α_{2i}=0 (Model 6). In the model, the constant returns to scale assumption is also imposed:

$$\ln(Y_{cit} / L_{cit}) = m_c + m_i + \lambda_i t + \alpha_{1i} \ln(K_{cit} / L_{cit}) + \varepsilon_{cit} \tag{B4}$$

Tables and Figures

Figure 1: TFP Index of 15 OECD countries (1987-2001, weighted average)

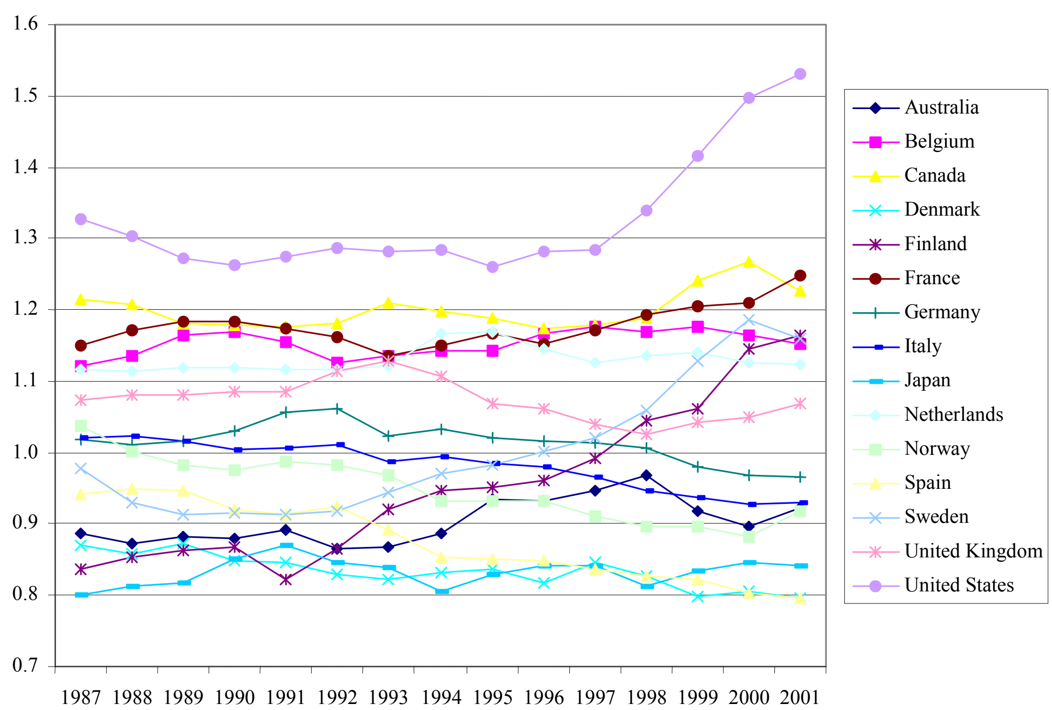

Table 1. Spillover Estimations (Non-linear Least Squares)

Data: 15 countries, year 1987-2001, and 13 industries (2,925 observations)
Dependent variable: Total Factor Productivity (TFP) Index

	Specification 1 (No spillover)		Specification 2 (No spillover)		Specification 3 (Geographic Spillovers)		Specification 4 (Technology Spillovers)	
Type of R&D stock	Business R&D		National R&D		Business R&D		Business R&D	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
TFP elasticity (α)	0.1327	17.928	0.1214	15.967	0.1762	18.152	0.1889	19.674
Strength of Spillovers (β)					0.0004	1.874	0.0001	4.413
Distance (γ)					1.0957	2.021		
Technology Distance (φ)							0.2464	4.540
Country-Industry Dummy (*dci*)	yes		yes		yes		yes	
Time Dummy (*dt*)	yes		yes		yes		yes	
R-square	0.824		0.820		0.829		0.833	
Log-Likelihood	2913		2880		2949		2987	
SIC	-1.418		-1.396		-1.438		-1.464	

Table 2: Quantity of various Knowledge Capital (1997, R&D stock)

(million 1997 PPP $US)

	(1): Business Knowledge (S1)		(2): National Knowledge (S2)		
	1997 $US	Share (%)	1997 $US	%Δ from (1)	Share (%)
Australia	18464	0.91	40646	120.14	1.38
Belgium	19901	0.98	27546	38.42	0.94
Canada	43500	2.15	78337	80.08	2.67
Denmark	9123	0.45	16696	83.02	0.57
Finland	10861	0.54	17565	61.72	0.60
France	132211	6.54	214665	62.37	7.31
Germany	218637	10.82	315682	44.39	10.75
Italy	59462	2.94	107023	79.99	3.64
Japan	412588	20.42	577034	39.86	19.65
Netherlands	29002	1.44	52713	81.76	1.79
Norway	7224	0.36	12620	74.69	0.43
Spain	18480	0.91	35958	94.58	1.22
Sweden	30458	1.51	43043	41.32	1.47
UK	112537	5.57	166350	47.82	5.66
US	898449	44.46	1231261	37.04	41.92
G5	1774422	87.80	2504993	41.17	85.29
Non-G5	246475	12.20	432148	75.33	14.71

	(3): Geographic Spillovers (S3)			(4): Technology Spillovers (S4)		
	1997 $US	%Δ from (1)	Share (%)	1997 $US	%Δ from (1)	Share (%)
Australia	18467	0.01	0.77	37256	101.78	1.44
Belgium	31271	57.14	1.31	27456	37.96	1.06
Canada	87700	101.61	3.68	70160	61.29	2.71
Denmark	12949	41.95	0.54	12981	42.29	0.50
Finland	12867	18.47	0.54	15050	38.56	0.58
France	178967	35.36	7.51	173054	30.89	6.68
Germany	293963	34.45	12.33	279826	27.99	10.80
Italy	83108	39.77	3.49	94288	58.57	3.64
Japan	412612	0.01	17.31	525232	27.30	20.27
Netherlands	45686	57.53	1.92	43652	50.52	1.68
Norway	9314	28.92	0.39	9908	37.15	0.38
Spain	31500	70.46	1.32	42444	129.68	1.64
Sweden	35016	14.97	1.47	36297	19.17	1.40
UK	170579	51.58	7.16	168663	49.87	6.51
US	959194	6.76	40.25	1055053	17.43	40.71
G5	2015315	13.58	84.56	2201829	24.09	84.97
Non-G5	367879	49.26	15.44	389491	58.02	15.03

Notes: (1) Business Knowledge is developed from real business R&D series from 1987 to 2001.
(2) Public Knowledge includes R&D expenditure of Government and Higher Education.
(3) Knowledge capital is converted into 1997 $US (Purchasing Power Parity).
(4) Set the year 1997 as the base year of business investment deflators.
(5) "%Δ from (1)" indicates % change from case (1).

Table 3. Estimations of Production Functions (with robust standard errors)

Data: 15 countries, year 1987-2001, and 13 industries (2,925 observations)
Dependent variable: log(GDP/Labor)

		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
		(No restrictions)		(CRS/R&D stock)		(CRS/R&D stock)		(CRS/R&D stock)		(CRS/R&D stock)		(CRS)	
Type of R&D stock		Business (S1)		Business (S1)		National (S2)		Geography (S3)		Technology (S4)		-	
TFP (US=1)	Australia	0.696		0.711		0.681		0.725		0.709		0.659	
(Country-Dummy)	Belgium	0.891		0.916		0.914		0.890		0.910		0.893	
	Canada	0.988		1.020		0.997		0.992		1.016		0.963	
	Denmark	0.724		0.750		0.733		0.733		0.749		0.702	
	Finland	0.715		0.734		0.724		0.731		0.727		0.708	
	France	0.927		0.940		0.925		0.920		0.937		0.924	
	Germany	0.811		0.818		0.815		0.804		0.814		0.796	
	Italy	0.838		0.850		0.831		0.842		0.853		0.775	
	Japan	0.646		0.646		0.644		0.651		0.645		0.632	
	Netherlands	0.950		0.982		0.961		0.955		0.978		0.962	
	Norway	0.781		0.798		0.784		0.784		0.790		0.793	
	Spain	0.754		0.777		0.759		0.770		0.781		0.679	
	Sweden	0.779		0.797		0.792		0.786		0.790		0.793	
	UK	0.857		0.867		0.861		0.851		0.865		0.830	
	US	1.000		1.000		1.000		1.000		1.000		1.000	
		coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
log(Labor)	Food Products	0.032	2.404										
	Textiles	-0.041	-3.452										
	Wood Products	-0.055	-4.036										
	Paper Products	0.023	1.638										
	Chemicals	0.009	0.690										
	Rubber and Plastics	-0.028	-2.273										
	Non-Metallic Products	-0.014	-1.145										
	Basic Metals	-0.040	-2.517										
	Fabricated Metals	-0.007	-0.619										
	Machinery	0.002	0.195										
	Electrical Equipment	-0.006	-0.506										
	Motor Vehicles	0.054	5.637										
	Other Transportation	-0.026	-1.604										
log(Capital/Labor)	Food Products	0.284	9.255	0.211	7.132	0.210	7.075	0.222	7.272	0.202	6.741	0.232	6.791
	Textiles	0.257	11.070	0.333	19.520	0.329	19.222	0.333	18.954	0.322	18.682	0.329	19.320
	Wood Products	0.112	5.339	0.155	6.720	0.159	6.809	0.166	7.028	0.160	6.864	0.163	7.397
	Paper Products	0.244	8.292	0.198	7.173	0.196	7.460	0.219	7.740	0.187	6.741	0.191	7.179
	Chemicals	0.148	4.217	0.126	3.533	0.104	2.875	0.142	3.906	0.127	3.523	0.204	5.458
	Rubber and Plastics	0.116	5.926	0.163	11.015	0.167	11.086	0.169	11.418	0.165	11.258	0.159	9.592
	Non-Metallic Products	0.147	8.578	0.159	11.374	0.165	11.590	0.166	11.512	0.160	11.271	0.168	12.804
	Basic Metals	0.261	11.253	0.253	10.163	0.230	9.266	0.253	10.477	0.248	10.152	0.345	10.138
	Fabricated Metals	0.235	6.137	0.234	6.249	0.236	6.158	0.210	6.261	0.225	6.137	0.238	5.899
	Machinery	0.097	5.399	0.103	5.892	0.108	6.686	0.092	5.273	0.102	5.866	0.128	9.036
	Electrical Equipment	0.286	6.783	0.281	6.686	0.292	7.011	0.279	6.424	0.279	6.726	0.389	9.253
	Motor Vehicles	0.073	6.226	0.032	2.070	0.040	2.616	0.020	1.261	0.031	2.072	0.056	3.841
	Other Transportation	0.146	6.911	0.156	7.818	0.154	7.931	0.155	8.102	0.156	7.885	0.224	10.714
log(R&D stock/Labor)	Food Products	0.089	7.370	0.077	6.302	0.080	6.108	0.090	5.556	0.108	6.629		
	Textiles	-0.022	-2.192	0.003	0.389	0.006	0.738	0.027	2.228	0.045	2.980		
	Wood Products	0.039	4.113	0.041	4.084	0.036	3.617	0.046	3.644	0.061	3.648		
	Paper Products	0.006	0.689	0.010	1.172	0.000	-0.017	0.007	0.578	0.042	2.743		
	Chemicals	0.135	7.688	0.150	8.300	0.179	8.716	0.153	7.395	0.150	8.319		
	Rubber and Plastics	0.009	0.914	0.017	1.670	0.020	1.803	0.014	1.272	0.021	1.927		
	Non-Metallic Products	0.021	2.276	0.029	3.217	0.021	2.075	0.044	4.241	0.037	3.725		
	Basic Metals	0.178	7.745	0.190	8.449	0.210	8.566	0.215	8.923	0.211	8.937		
	Fabricated Metals	0.118	7.148	0.127	8.139	0.123	7.815	0.179	8.818	0.189	8.900		
	Machinery	0.060	4.116	0.062	4.256	0.051	3.194	0.093	5.450	0.065	4.416		
	Electrical Equipment	0.164	6.771	0.167	7.115	0.148	5.950	0.175	8.105	0.188	7.724		
	Motor Vehicles	-0.014	-1.204	0.047	3.967	0.036	2.929	0.087	4.597	0.047	3.979		
	Other Transportation	0.090	5.448	0.077	6.138	0.078	5.933	0.096	7.864	0.076	6.039		
Country Dummy		yes		yes		yes		yes		yes		yes	
Industry-specific Trend Dummy		yes		yes		yes		yes		yes		yes	
Industrial Dummy		yes		yes		yes		yes		yes		yes	
R-square		0.853		0.842		0.842		0.844		0.843		0.822	
Log-Likelihood		1564		1456		1455		1472		1466		1280	
SIC		-0.854		-0.815		-0.815		-0.826		-0.823		-0.731	

Table 4. Results of Strict HOV Models (Year 1997)

A. HOV Model: 15 observations (across country)

	Capital	Labor	R&D Stocks (S1) Business	R&D Stocks (S2) National (+Public)	R&D Stocks (S3) Spillover (Geography)	R&D Stocks (S4) Spillover (Technology)
Sign Test	0.667	0.467	0.733	0.800	0.800	0.933
Slope Test	0.021	0.019	0.401	0.541	0.316	0.432
standard error	0.012	0.020	0.113	0.093	0.114	0.063
R-squared	0.173	-0.003	0.473	0.703	0.352	0.766
Variance Test	0.002	0.006	0.337	0.412	0.278	0.241

B. The Pair-Wise HOV Model: 105 observations (across country-pair)

	Capital	Labor	R&D Stocks (S1) Business	R&D Stocks (S2) National (+Public)	R&D Stocks (S3) Spillover (Geography)	R&D Stocks (S4) Spillover (Technology)
Sign Test	0.581	0.457	0.810	0.829	0.762	0.848
Slope Test	0.055	-0.097	0.401	0.412	0.295	0.415
standard error	0.033	0.024	0.043	0.051	0.049	0.040
R-squared	-0.015	0.101	0.441	0.370	0.239	0.502
Variance Test	0.115	0.069	0.343	0.426	0.325	0.327

Notes: (1) Sign test is sign concordance probability: sign=the number of sign fits/the number of observations.

(2) Slope test regresses Fc by V_c-$s_c V_w$ without an intercept.

(3) Variance test is (variance in the measured factor contents of trade)/(variance in predicted factor contents of trade).

Table 5. Estimations of Factor-Productivities (with robust standard errors)

Data: 15 countries and year 1987-2001 (225 observations)
Dependent variable: Factor-Productivities

	Capital-Productivity				Labor-Productivity			
Type of R&D stock	Business R&D (S1)		Spillover (S4)		Business R&D (S1)		Spillover (S4)	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Knowledge/Capital (σ_{1k})	0.235	10.085	0.256	10.534				
Labor/Capital (σ_{2k})	0.720	39.337	0.708	33.407				
Knowledge/Labor (σ_{1L})					0.173	12.901	0.215	15.006
Capital/Labor (σ_{2L})					-0.016	-0.998	-0.015	-1.008
Time Dummy (h_t)	yes		yes		yes		yes	
Country-Dummy (h_c)	yes		yes		yes		yes	
R-square	0.945		0.945		0.975		0.975	
Log-Likelihood	427		426		492		492	
SIC	0.289		-3.038		-3.631		-3.631	

Figure 2-1. Business R&D stock

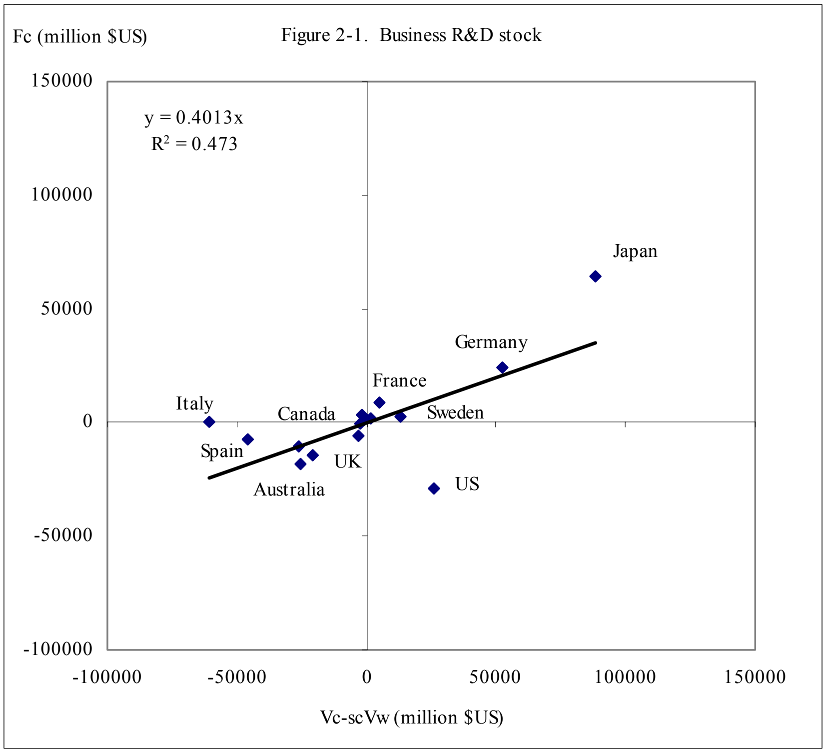

Figure 2-2. Business R&D + Technology Spillovers

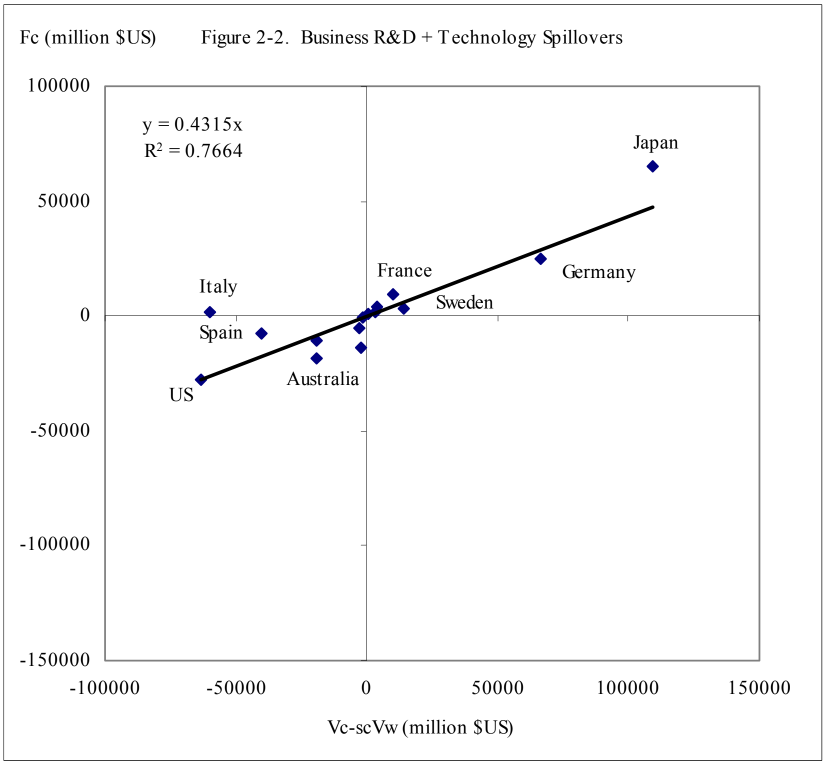

Table 6. Results of the HOV models with Productivity Adjustments (Year 1997)

(1) TFP Adjustments

A. HOV Model

	Business R&D Stock (S1)				Technology Spillovers (S4)			
	Total	Capital	Labor	R&D	Total	Capital	Labor	R&D
Sign Test	0.578	0.600	0.400	0.733	0.600	0.600	0.400	0.800
Slope Test	0.078	0.083	-0.063	-0.117	0.081	0.084	-0.063	-0.125
standard error	0.019	0.026	0.031	0.132	0.019	0.026	0.031	0.179
R-squared	0.273	0.416	0.170	0.048	0.283	0.415	0.172	0.027
Variance Test	0.022	0.016	0.017	0.257	0.023	0.016	0.016	0.461

B. The Pair-Wise HOV Model

	Business R&D Stock (S1)				Technology Spillovers (S4)			
	Total	Capital	Labor	R&D	Total	Capital	Labor	R&D
Sign Test	0.619	0.657	0.448	0.752	0.619	0.657	0.429	0.771
Slope Test	0.419	0.421	0.040	0.370	0.414	0.418	0.035	0.339
standard error	0.029	0.048	0.028	0.070	0.029	0.050	0.028	0.068
R-squared	0.401	0.396	-0.016	0.190	0.383	0.378	-0.021	0.172
Variance Test	0.429	0.405	0.085	0.626	0.438	0.416	0.085	0.581

(2) Factor-Productivity Adjustments

A. HOV Model

	Business R&D Stock (S1)				Technology Spillovers (S4)			
	Total	Capital	Labor	R&D	Total	Capital	Labor	R&D
Sign Test	0.756	0.733	0.800	0.733	0.822	0.733	0.800	0.933
Slope Test	0.206	0.150	0.068	0.401	0.238	0.159	0.111	0.432
standard error	0.070	0.122	0.136	0.113	0.064	0.123	0.139	0.063
R-squared	0.164	0.076	-0.050	0.473	0.236	0.085	-0.022	0.766
Variance Test	0.255	0.226	0.248	0.337	0.239	0.232	0.265	0.241

B. The Pair-Wise HOV Model

	Business R&D Stock (S1)				Technology Spillovers (S4)			
	Total	Capital	Labor	R&D	Total	Capital	Labor	R&D
Sign Test	0.759	0.743	0.724	0.810	0.771	0.733	0.733	0.848
Slope Test	0.574	0.631	0.571	0.401	0.579	0.634	0.554	0.415
standard error	0.053	0.103	0.057	0.043	0.053	0.103	0.055	0.040
R-squared	0.265	0.234	0.470	0.441	0.272	0.237	0.473	0.502
Variance Test	1.213	1.454	0.646	0.343	1.200	1.447	0.604	0.327