THREE EMPIRICAL STUDIES ON INTERNATIONAL TRADE

BY

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Chapter 1

The Factor Content of Bilateral Trade: An Empirical Test (with Pravin Krishna)

1.1 Introduction

The Factor Proportions model, which predicts that international trade is driven by differences in factor endowments between countries, is one of the most influential theories in international economics. In addition to being used in the study of trade flows between countries, this model has also served as a platform for innumerable academic and policy analyses in international trade. These range from the study of the impact of trade on income inequality within and between countries to the analysis of the implications of foreign direct investment on welfare and the impact of immigration on production patterns, *inter alia*.

This central standing of the Factor Proportions model in international economics has appropriately prompted, particularly recently, intense empirical scrutiny.[1] Researchers testing this framework have largely focused on an elegant prediction of the

[1]See Leamer and Levinsohn (1995), Helpman (1998), and Davis and Weinstein (2001) for comprehensive discussions.

model relating to net factor content of trade that obtains in even its multicountry, multifactor and multicommodity version: the well-known Heckscher-Ohlin-Vanek (HOV) prediction. This holds that under the assumptions that technologies everywhere are identical, that trade equalizes factor prices worldwide and that consumer preferences everywhere are identical and homothetic, the net exports of factors by a country will equal the abundance of its endowment of these factors relative to the country's world income share. Early tests of the HOV prediction in its strict form, however, proved very disappointing for the theory: In a widely-cited and pioneering study, Bowen, Leamer and Sveikauskas (1987) reported that the direction of net factor content flows among twenty-seven countries were predicted as well (or better) by a coin toss as by the theory – a finding that established a mood of deep pessimism with regard to the empirical validity of the model.[2]

This apparent failure of the theory (in its strict form) to match the data led researchers to amend the theory and to improve on the data used in the empirical exercises.[3] In a series of remarkable contributions, Trefler (1993, 1995) and Davis and Weinstein (2001) variously attempted particular modifications (some systematic and some ad hoc) of the basic HOV assumptions and tested the resulting predictions to find much stronger support for the theory. Thus, Trefler (1995) reported that

[2]Other trade related predictions of the Factor Proportions theory did not fare much better: In a very well-known contribution, Leontief (1953) used data on the factor content of U.S. exportables and importables to find "paradoxically" that the former used more labor relative to capital than the latter in its production, thus rejecting the central prediction of the Factor Proportions model - that countries export goods which use more intensively their abundant factors.

[3]Also, a growing literature has examined other aspects and predictions of the neoclassical trade model: Prominent recent contributions include Harrigan (1995, 1997), Hanson and Slaughter (1999), Schott (1999) and Bernstein and Weinstein (1998), among others.

a variation of the model that postulated Hicks-neutral factor efficiency differences across country groups performed very well against the standard HOV prediction. And Davis and Weinstein (2001) articulated a series of additional departures from the basic HOV framework, including the use of bilateral trade estimates from the so-called "gravity equations" (themselves valid under the further assumptions of perfect specialization in tradables and specific assumptions on preferences) to account for the role of trade costs in restricting trade, to also report much stronger support for the theory.[4]

Our paper contributes to this literature on empirical testing of the Factor Proportions theory. Our methodology contrasts strongly with nearly all earlier work, however. Nearly all of the tests of the factor content predictions of the model (including the ones we have discussed above) have assumed full factor price equalization across countries (FPE) and identical homothetic preferences across countries (i.e., they have tested the HOV prediction) or have attempted very specific relaxation of these joint assumptions – for instance, by allowing for factor price differences to result from Hicks-neutral factor efficiency differences across countries, as in Trefler (1995). In contrast, this paper implements a test of restrictions implied by the theory (derived originally by Helpman (1984)) on the factor content of trade which rely on neither FPE nor on *any* restrictions on preferences. We consider this to be a significant step because, as Helpman (1998) has noted, even casual evidence

[4]The work of Davis and Weinstein (2001) is additionally remarkable from the standpoint of the data used. While the vast majority of papers in the literature used US "technology" matrices to proxy for technology matrices in the rest of the world, Davis and Weinstein (2001) used data on actual technology matrices for all OECD countries. This is an enormous data compilation and organization effort that has changed forever the standards on data usage in this area.

suggests that full FPE does not hold (as we know from data on wages) and that preferences are non-homothetic and vary substantially with income level. A further and equally important contrast with the existing literature derives from the fact that while most empirical tests of the theory (and tests of HOV in particular) have focused on the net factor content of a country's *multilateral* trade, our tests concern *bilateral* trade flows, thereby enabling the examination of trade flows between only a subset of countries for which quality data (relatively speaking) is available.

Helpman (1984)'s result, itself an intuitive (and general) formalization of some earlier work by Brecher and Choudhri (1982), is both straightforward and powerful: even in the absence of FPE, with identical technologies across countries, it is a simple matter to observe that the more capital rich a country is, the more capital and less labor it uses in all lines of production, while correspondingly achieving a higher wage-rental ratio. Hence, whatever trade exists between two countries, exports of the capital rich country will embody a higher capital-labor ratio than the exports of the relatively labor rich country. This, in turn, describes a clear *bilateral* factor content of trade. Specifically, the theory implies that, *on average*, a country imports those factors that are cheaper in the partner country and is a net exporter of those factors that are more expensive there. It is this description that we test using data on OECD production and trade flows. It is worth noting that the theoretical restrictions that we test here are easily extended to accommodate the possibility of technological differences across countries. We discuss this extension in Appendix A.2. where we also present the corresponding theoretical derivation to take into account this factor.

The rest of the paper is structured as follows: Section 1.2 presents the basic Helpman (1984) result regarding restrictions on bilateral trade flows, incorporating additionally the use of intermediates in production into the analysis. We discuss the advantages and disadvantages of testing these restrictions over standard HOV tests. Section 1.3 describes the data. Section 1.4 describes our empirical analysis and the results. Section 1.5 concludes. Appendix A.1. provides a detailed description of the data. Appendix A.2. discusses extensions to take account of Hicks-neutral technological differences across countries.

1.2 Theory

Our analysis considers a freely trading world with many goods and countries in which production technology is convex, the technology for producing any good is assumed (for now) identical across countries, and perfect competition characterizes both goods and factor markets.

In this framework, as we have noted before, Helpman (1984) derived intuitive restrictions on the factor content of bilateral trade between countries – relating factor content trade to relative factor scarcities in the trading countries. The basic insight behind Helpman (1984)'s result can be easily explained using a Lerner diagram. Figure 1.1 depicts a Lerner diagram for the two factor - six goods - three country case.

The isoquants in Figure 1.1, numbered from 1 to 6, describe output levels of goods 1 to 6 respectively, each worth a dollar at free trade prices. The factors used in the production of these goods are capital and labor. The capital-labor ratios of the

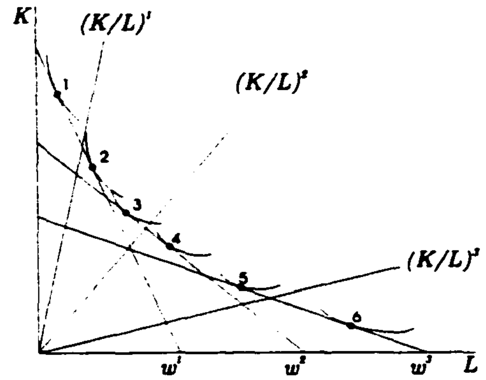

Figure 1.1: Lerner Diagram

three countries are represented by the rays $(K/L)^c$, and their free trade wage-rental ratios are represented by the slopes ω^c, $c = 1, 2, 3$. In the equilibrium described above, country 1, which has the highest capital-labor ratio, produces goods 1 and 2; country 2, with an intermediate capital-labor ratio, produces goods 3 and 4; and country 3, with the lowest capital-labor ratio, produces goods 5 and 6. It is a simple matter then to observe that the more capital rich a country is, the more capital and less labor it uses per dollar output in all lines of production. Hence, whatever trade takes place between any two countries, the exports of the relatively capital-rich country will embody a higher capital-labor ratio than the exports of the relatively labor-rich country. This in turn describes a clear bilateral factor content pattern of trade even in the absence of factor price equalization and any assumption regarding preferences.

In what follows, we present Helpman (1984)'s result allowing additionally for the presence of intermediate goods in production. It is worth noting that, even under the maintained assumption of identical technologies across countries, non-equalization of factor prices will still result in different techniques of production being used across countries. We denote the direct input matrix, which indicates how much direct input of each factor is required to produce one dollar of gross output within each industry, for any country c, by $\mathbf{A}^c$. The input-output matrix for country c, indicating the amount of output each industry must buy from other industries to produce one dollar of its gross output, Y^c, is denoted by $\mathbf{B}^c$. For any country c, the trade vector ($\mathbf{T}^c$) is the difference between net production ($\mathbf{Q}^c$) and consumption ($\mathbf{C}^c$):

$$\mathbf{T}^c = \mathbf{Q}^c - \mathbf{C}^c. \tag{1.1}$$

In the presence of intermediates in production, we have,

$$\mathbf{Q}^c = (\mathbf{I} - \mathbf{B}^c)\mathbf{Y}^c. \tag{1.2}$$

Since $\mathbf{A}^c(\mathbf{I} - \mathbf{B}^c)^{-1}$ is then the matrix of total (direct and indirect) factor inputs required to produce one dollar of net output in each industry (i.e., it is the overall technology matrix in the presence of intermediate goods), the factor content of the trade flow, $\mathbf{T}^c$, on the left hand side of (1.1) can be determined by pre-multiplying $\mathbf{T}^c$ by $\mathbf{A}^c(\mathbf{I} - \mathbf{B}^c)^{-1}$. Thus, for any *bilateral* trade between two countries, c' and c, we can write

$$\mathbf{T}_V^{c'c} = \mathbf{A}^c(\mathbf{I} - \mathbf{B}^c)^{-1}\mathbf{T}^{c'c}, \tag{1.3}$$

where $\mathbf{T}^{c'c}$ is the gross *import* vector by country c' from country c and thus $\mathbf{T}_V^{c'c}$ is the gross *import* vector of factor content by country c' from country c.

Now, by the definition of the revenue function, we know that for country c', $\Pi(\mathbf{p}, \mathbf{V}^{c'}) = \mathbf{p}\mathbf{Q}^{c'}$, where Π is a revenue function representing production technology, $\mathbf{V}^{c'}$ is the endowment vector in country c' and $\mathbf{p}$ is the commodity price vector in the free trade equilibrium.[5] Given the assumption of identical technologies across countries, it should be clear that if country c' is given its gross import of factor content ($\mathbf{T}_V^{c'c}$) as an extra amount of factor endowment, it could produce with it at least the value of gross imports ($\mathbf{pT}^{c'c}$). This and the concavity of $\mathbf{\Pi}$ in $\mathbf{V}$ (used to arrive at the second inequality in what follows) give us that,

$$\begin{aligned} \mathbf{p}(\mathbf{Q}^{c'} + \mathbf{T}^{c'c}) &\leq \mathbf{\Pi}(\mathbf{p}, \mathbf{V}^{c'} + \mathbf{T}_V^{c'c}) \\ &\leq \mathbf{\Pi}(\mathbf{p}, \mathbf{V}^{c'}) + \mathbf{\Pi}_V(\mathbf{p}, \mathbf{V}^{c'})\mathbf{T}_V^{c'c} \\ &= \mathbf{pQ}^{c'} + \mathbf{w}^{c'}\mathbf{T}_V^{c'c}, \end{aligned} \tag{1.4}$$

where $\mathbf{\Pi}_V$ is the vector of partial derivatives of $\mathbf{\Pi}$ with respect to $\mathbf{V}$ and $\mathbf{w}^{c'}$ is the factor price vector in country c'.

Eliminating $\mathbf{pQ}^{c'}$ from both sides of (1.4) in turn gives us

$$\mathbf{pT}^{c'c} \leq \mathbf{w}^{c'}\mathbf{T}_V^{c'c}. \tag{1.5}$$

Further, in country c, since perfect competition implies that every line of production must break even in equilibrium, we have,

$$\mathbf{pT}^{c'c} = \mathbf{w}^{c}\mathbf{T}_V^{c'c}. \tag{1.6}$$

Combining (1.5) and (1.6) yields the following inequality,

$$(\mathbf{w}^{c'} - \mathbf{w}^{c})\mathbf{T}_V^{c'c} \geq 0. \tag{1.7}$$

Similarly, for c's imports, we have,

$$(\mathbf{w}^{c'} - \mathbf{w}^{c})\mathbf{T}_V^{cc'}. \leq 0 \tag{1.8}$$

[5]Note that our assumption of identical production functions across countries implies that the revenue function is also common across countries (and we therefore have no country-superscript for the revenue function).

Equations (1.7) and (1.8) together yield,

$$(\mathbf{w}^{c'} - \mathbf{w}^{c})(\mathbf{T}_V^{c'c} - \mathbf{T}_V^{cc'}) \geq 0. \tag{1.9}$$

As Helpman (1984) has pointed out, (1.9) may be interpreted as implying that, on *average*, country c' is a net importer from country c of the content of those factors of production that are cheaper in c than in c' and vice versa.[6] It should be readily evident that all the variables in (1.9) relate to the equilibrium *with* trade. (1.9) may therefore be tested using data from the trade equilibria that we "observe." This is precisely what the rest of our analysis attempts to do. In implementing tests of (1.9), one needs to take into account the important observation of Staiger (1986) that when intermediates are freely traded, Helpman's measure of the bilateral factor content of trade needs to be modified to exclude the factor content of traded intermediate goods. Therefore, we perform the tests described above using input-output matrices that include only domestically produced intermediates.[7]

Our discussion so far has assumed identical technologies across countries. It is worth noting here that a relationship quite close to (1.9) may be easily derived even if technologies are *not* identical across countries. Consider the case when technologies are instead characterized by Hicks-neutral differences across countries, where a country c is uniformly more productive than country c' in the production of every good by a (potentially measurable) factor λ. The logic underlying the derivation

[6]It is tempting to interpret (1.9) as a measure of the savings in production costs in country c' due to the fact that the gross import vector $\mathbf{T}^{c'c}$ is imported rather than domestically produced (measured at equilibrium factor prices in the domestic country. This is however incorrect. The cost savings from importing rather than producing domestically, crudely speaking, require a comparison of autarky equilibria with equilibria with trade. This is not what is being compared in (1.9).

[7]See Appendix A.1. for a detailed discussion and a simple example illustrating the need for the modification of Helpman's measure as suggested by Staiger (1986).

of (1.4) still holds - with the difference that if country c' is given its gross import of factor content ($\mathbf{T}_V^{c'c}$) as an extra amount of factor endowment, it could produce with it at least the value of gross imports ($\mathbf{p}\mathbf{T}^{c'c}$) times the ratio $\frac{1}{\lambda}$. Equations (1.5) through (1.9), *mutatis mutandis*, are then easily derived. Alternately, we may allow for Ricardian differences in technology across countries, where technology in industry i in c is more productive than the same industry i in c' by a factor of λ_i. Expressions analogous to (1.9) (now involving the full set of λ_i's for every industry) may be easily derived. We develop these expressions in detail in Appendix A.2., where we also provide test results for the subset of countries for which we have data on relative industrial productivities (the λ_i's).

We have derived here theoretical restrictions on the factor content of bilateral trade flows that may be tested using "observable" data. These tests offer significant advantages over the HOV-based tests that currently dominate the literature — but also suffer from some disadvantages. The primary advantages are that the restrictions that we have derived do not require that factor prices be equalized across countries and do not require any assumptions on consumer preferences. Both of these are significant relaxations of the theoretical assumptions under which most HOV-based testing of the factor proportions model has been conducted (from both a theoretical and an empirical perspective, as we have previously discussed). Further, while most empirical tests of the theory (and tests of HOV in particular) have focused on the net factor content of a country's *multilateral* trade, our tests concern *bilateral* trade flows, thereby enabling the examination of trade flows between only a subset of countries for which quality data (relatively speaking) is available. Finally, extensions of tests to allow for differences in production technologies across countries (including Ricardian, industry specific differences), while infeasible in the HOV context, are straightforward here. The disadvantages of the tests proposed here, on the other hand, are as follows: While HOV-based tests provide *exact* predictions regarding the factor content of trade in each factor, our tests provide only a statement regarding the direction and magnitude of the flow of factors, on *average*. Further, while HOV tests require information on trade and technology from the entire trading world, they permit us to focus on only those factors in which we are interested or on which we have data. In contrast, the tests proposed here require information on all factors of production (so that the value of produced output is split among the factors of production considered). Thus, the tests conducted here offer some significant theoretical and implementation advantages over HOV tests but are also inferior to HOV tests in some respects. The two approaches should largely be seen as complements.

1.3 Data Sources

The countries we consider in this study are Canada, Denmark, France, Germany, Korea, Netherlands, the UK and the US. In order to test the restrictions (1.7)-(1.9) for any pair of these countries, we need data on the factor price vector ($\mathbf{w}$), the direct input matrix ($\mathbf{A}$), and the input-output matrix ($\mathbf{B}$) for each country in the pair, as well as the gross bilateral import vectors ($\mathbf{T}$) that describe trade flows between them.

Most previous work that implemented tests of the factor proportions theory has generally assumed (and used) the same technology matrices (**A** and **B**) across countries (usually U.S. technology matrices) in order to calculate the factor content of trade of any country – mostly due to the general difficulty of obtaining the relevant data for a cross-section of countries at any given time.[8] Under the maintained assumptions of FPE as well as identical technologies across countries, the use of the same technology matrices to represent production in different countries does not create any problems at the theoretical level. In contrast, because we choose to abandon the assumption of FPE, we are forced to confront the fact that, at the theoretical level itself, different technology matrices across countries are implied even under the maintained assumption of identical technologies across countries. To this end, this study has required the collection of technology data on both the direct input matrices as well as the input-output matrices for each country. As noted earlier, taking trade in intermediates into account implies that we need to use input-output matrices that only include the usage of domestically produced intermediates – since Helpman's measure of the bilateral factor content of trade needs to be modified to exclude the factor content of traded intermediate goods (as Staiger (1986) has pointed out). Details on the relevant technology matrices that we used are provided in the Appendix A.1. at the end of this paper.

The factor price data that we used in this paper were put together from a variety of sources. Details on the original data sources and our processing of this data in

[8]Some exceptions may be noted: Trefler (1993), while assuming that the U.S. technology matrix was basically valid for all countries, rescaled each by a country-specific productivity parameter. Hakura (1999) used the data of direct input matrices as well as input-output matrices for each of the five European countries. Davis and Weinstein (2001) was the first study which used the same data set as ours: the OECD Input-Output Database.

order to arrive at internationally comparable factor price vectors are described below (with some additional details provided in the Appendix A.1.).

For the purposes of empirical implementation, production technology was assumed to admit two types of primary input factors: capital and (dis-aggregated) labor. In compiling the data for our analysis, one issue that arose was the lack of availability of internationally comparable data on factor prices. A second and equally compelling problem was that the factor price data that was reported was sometimes inconsistent with GDP data (i.e., the inner product of factor prices and the factor endowment vector does not sum to GDP).

Our strategy in dealing with these problems was to collect factor price data from various sources which were perhaps not directly comparable in the first instance, and then to process it so as to get comparability across nations *and* a match with GDP data. This was achieved as follows: the Annual National Account (ANA) Database of the OECD provides data on cost components of GDP where GDP is decomposed into the following terms: compensation of employees (CE), operating surplus (OS) and an aggregate of other components (OC) such as indirect taxes and subsidies. To achieve consistency of the factor price data with national income accounts, we started first with returns to aggregates (of labor and capital) and then moved on to dis-aggregated returns. Thus, to begin with, we require that the total return to labor in any country be equal to its CE, i.e., we *set* CE $= \sum_i w_i L_i$, where the summation is across dis-aggregated labor categories.

To determine the total return to capital we have two options: the first (henceforth referred to as the Capital I method) is to let the operating surplus equal the ex-post return to capital in the economy (i.e., to set OS $= rK$).[9] A second option (henceforth referred to as the Capital II method) is to let

$$\text{GDP} - \sum_{i=1}^{n} w_i L_i = rK$$

that is, to let the return to capital equal the residual when employee compensation is taken out of GDP. We perform our tests using both methods for calculation of the total return to capital.

Given the overall compensation to labor ($\sum_i w_i L_i$) and the overall return to capital, we need next the returns to dis-aggregated labor. This was accomplished in the following manner. Endowments of labor in various occupations (L_i) and the occupational wage rates (w_i) were directly obtained from various national statistical publications for three non-European countries and from Eurostat's Structure of Earnings for the five European countries in our data set. There are two problems with using this data directly. First, there is the issue of overall consistency with the national income accounts because the value of $\sum_i w_i L_i$ rarely equals the CE data reported in the national income accounts. In order to achieve this consistency, we *construct* a modified series of wage rate data as follows. Given the observed data on occupational wage rate (w_i), occupational employments (L_i) and compensation of employees (CE), we calculated the modified wage rate ($\hat{w}_i$) for each occupation by solving

$$\sum_{i=1}^{n} \hat{w}_i L_i = CE \quad \text{and} \quad \frac{w_i}{w_j} = \frac{\hat{w}_i}{\hat{w}_j}, \ \forall i, j \in n$$

[9]To set operating surplus equal to rK requires a strong zero-profit assumption because, in general, the operating surplus contains other components, such as profit, as well.

That is, we took the information about the wage ratios between occupations from the reported wage series w_i and made the sum of constructed wage rates multiplied by occupational employment levels consistent with the measure of compensation of employees in the national accounts database.

A second issue had to do with comparability of labor classes across countries. Publications for different countries use different occupational classification systems.[10] Thus, some re-categorization of occupational classifications was inevitable. Data for each of the three non-European countries (Korea, Canada, and the United States) were reported in a manner conforming closely to what is referred to as the ISCO (Industrial Standard Classification of Occupation) 1968 system. However, the occupational classifications of European countries in their structure of earnings data (as reported in Eurostat) were quite different from those of the non-European countries and could not have been recategorized easily into the ISCO 1968 system. Also, these were at a substantially higher level of aggregation than the data for the non-European countries. We considered two types of re-categorization. The first was simply to divide the labor force for all countries into production workers and non-production workers (henceforth Euro I categorization). The other one was to disaggregate the non-production workers into three categories; managerial, clerical and others (henceforth Euro II categorization).

The factor prices used in our empirical exercises are reported Table 1.1. Wages for both labor classifications – the Euro I and Euro II classifications described above – are presented in the upper panel. As can be seen from a comparison, say, of US

[10]For details on publication sources, see Appendix A.1

and German wages, there is a reasonable degree of divergence between even the OECD countries used in our analysis. Indeed, the wage gap between Korea and the rest of the OECD is extremely large, as the figures presented in Table 1.1 indicate. As we have discussed before, we have used primarily two measures of return to capital. Our first measure of the rental price of capital (Capital I method), as we previously discussed, was obtained by dividing the operating surplus by net capital stock. The lower panel in Table 1.1 reports rental price of capital calculated in this way for each country. Denmark has the lowest rental price of capital (5.3 percent), while the U.S. is a bit higher (8 percent) and Korea is the highest (15.5 percent). Our second measure of the return to capital (Capital II method) was obtained by taking the net return to capital to be the difference between GDP and CE and dividing this number by the net capital stock. This measure of return to capital, consistent with an overall division of GDP into rewards to labor and capital, is also reported in the second panel of Table 1.1. By the Capital II method, return to U.S. capital, for instance, is 16.5 percent and the return to capital in Korea is 23.37 percent. Since the Capital I measure is net of taxes on production (following the definition of "Operating Surplus") and the Capital II measure is gross of indirect taxes, the Capital I measure can be expected to be lower than the Capital II measure of return to capital. This can be seen from our calculations as well.

1.4 Results

Tests of our basic restriction on the factor content of bilateral trade flows, Equation (1.9), can be conducted using the factor price data and the country specific technology matrices whose construction we have described in the previous section. Since entering technology and factor price data into the left hand side of (1.9) would simply gives us an un-normalized numerical sum, whose extent of conformance or departure from the theory cannot be easily ascertained,[11] we first re-write (1.9) in the following manner:

$$\frac{\mathbf{w}^{c'}\mathbf{T}_V^{c'c} + \mathbf{w}^{c}\mathbf{T}_V^{cc'}}{\mathbf{w}^{c}\mathbf{T}_V^{c'c} + \mathbf{w}^{c'}\mathbf{T}_V^{cc'}} = \theta \geq 1 \tag{1.10}$$

(1.10) has a convenient interpretation. For any country pair, c and c', with gross bilateral import flows, $\mathbf{T}^{c'c}$ and $\mathbf{T}^{cc'}$, the ratio in (1.10) is the ratio of the sum of the importers' (hypothetical) cost of production (using domestic factor prices and imported factor content) to the total ("actual") cost of production in the exporting countries. Thus, the first term in the numerator of the ratio in (1.10), $\mathbf{w}^{c'}\mathbf{T}_V^{c'c}$, is the hypothetical cost of production of the gross import vector of c' from c, $\mathbf{T}^{c'c}$, using the factor prices in c', $\mathbf{w}^{c'}$, and the factor content actually employed in production of this import vector in the exporting country c, $\mathbf{T}_V^{c'c}$. The cost of producing these goods in the exporting country, c, is given by the first term in the denominator of the ratio in (1.10), $\mathbf{w}^{c}\mathbf{T}_V^{c'c}$. The second terms in the numerator and the denominator relate to the trade flow $\mathbf{T}^{cc'}$, the gross import vector of c from c', and are equal to the hypothetical cost of production in the importer of that flow c and the "actual" cost of production in the exporter c' respectively. We denote this ratio of costs as θ. Clearly, from (1.9) and (1.10), the theory predicts that $\theta \geq 1$. Importantly (and

[11]For instance, if for a given country pair, we were to obtain that the left hand side of (1.9) added up to -90,000, we would be able to conclude that the theoretical restriction that the left hand side be greater than zero had not been met, but would be unable to tell how significant a departure this is from the theory.

this is what has motivated our transition from (1.9) to (1.10)), given the relative cost interpretation for θ that we have provided above, actual measures of θ for any country pair will give us an intuitive sense of the extent of conformance or departure of the data from the theory for those countries.

We describe first the values of θ obtained using the raw factor price measures reported in Table 1.1. Results from additional simulation-based analyses that were conducted to take into account the fact that our factor price measures may be subject to measurement error are described subsequently. The values of θ calculated using the Euro I and Euro II labor classifications and the Capital I measure of return to capital are presented in Tables 1.2 and 1.3 respectively. Values calculated using the Capital II measure of return to capital instead are presented in Tables 1.4 and 1.5.

Consider the results presented in Tables 1.2 with the Euro I and Capital I factor price measures. Keeping in mind the theoretical prediction that $\theta \geq 1$, we can see that the theory is satisfied directly for twenty-one of the twenty-eight country pairs in our sample. Note that even for the seven pairs for which the theory is not satisfied, θ falls below 0.99 in only three cases. Table 1.3 presents values of θ calculated using Euro II and Capital I factor prices. The move from the Euro I classification to the more disaggregated Euro II classification does not seem to affect the results by much. The success rate for the theory stays about the same. Twenty-one of the twenty-eight country pairs satisfy the theory directly. Of the seven remaining pairs, only three fall below 0.99. Values of θ calculated using Capital II factor prices and Euro I labor classification are presented in Table 1.4. As the numbers presented there indicate, there is now a slight improvement in the extent to which the data are consistent with the theory. Specifically, twenty-two of the twenty-eight country pairs in our sample now satisfy the theory. Of the six remaining pairs, none fall below 0.99. Values with the Capital II and Euro II measures are equally supportive of the theory. Once again, twenty-two of the twenty-eight country pairs directly satisfy the theory. Of the rest, none fall below 0.99.

Overall, the results in Tables 1.2, 1.3, 1.4 and 1.5 appear to support the theory substantially. It is true that for any given combination of factor price measures, the data are inconsistent with the theory for roughly one quarter of the country pairs, as we have discussed above. However, a number of these "failures" are minor in magnitude – with the ratio θ being greater than 0.99 but less than 1 in a great proportion of these cases. To what extent could these failures be driven by simply measurement error in factor prices? To examine this, measurement error in factor prices can be modeled in the following fashion (an alternate methodology that gives nearly equivalent results is described in footnote 14 below):

$$w_{obs} = w_{true} + \epsilon_w, \quad \epsilon_w \; N(0, \sigma_w^2) \tag{1.11}$$

That is, the observed value of any given factor price, w_{obs}, can be assumed different from the true value of the factor price, w_{true}, by an amount equal to the measurement error ϵ_w where ϵ_w itself is assumed to be distributed normally with zero mean and variance σ_w^2. Consider a single factor price at a time. Taking the values of all other observed factor prices used in calculating the left hand side of (1.9) as being true, for the particular factor price being considered, w_{true} can be set equal to a value $\bar{w}$ so that the theory is just right (i.e., so that (1.9) is just satisfied).

Then taking a large number of draws of w_{obs} (10,000 draws in our exercises) under particular assumptions on the magnitude of σ_w (that, for instance, it is 5 percent of the value of w_{obs}), the left hand side of (1.9) can computed in each case and its distribution thus obtained. Given the calculation of (1.9) using observed factor prices, we can then ask if we can reject the null that the theory is right (i.e., that the left hand side of (1.9) ≥ 0). This can then be done for all factor prices for each country pair and the exercise repeated for every country pair so we can finally ask, how often we unable to reject that the theory is right.[12]

The results of these exercises are presented in Table 1.6 where the headers of the three columns indicate the extent of measurement error assumed in drawing w_{obs} – with σ_w equal to 2.5 percent, 5 percent and 10 percent of the mean of w_{obs} respectively. For a given combination of factor price measures chosen (say, Euro I and Capital II) the rows correspond to the significance level for the test. The entries in the table corresponding to a given level of significance and a given level of measurement error indicate the fraction of cases in which we were unable to reject that the theory is right.[13] As the figures in Table 1.6 indicate, allowing for

[12]A nearly equivalent exercise (in Bayesian spirit) treating all factor prices together would model the measurement error in factor prices in the following fashion:

$$w_{true} = w_{obs} + \theta_w, \quad \epsilon_w \; N(0, \sigma_w^2)$$

. Now, under assumptions regarding the magnitude of $sigma_w$ for each factor price, say that it equals 5 percent of

w_{obs}, we can take 10,000 draws on w_{true} for each of the factor prices. The left hand side of (1.9) can be computed in each of the 10,000 cases and the distribution of true value of the left hand side of (1.9) can be obtained. We can then examine where along this distribution the minimum acceptable value of (1.9) for the theory to be right (i.e., the number zero) lies. This would allow us to answer the question of how likely it is for the "truth" to lie in the acceptable region given our observations on factor prices. This exercise gives us answers that are quantitatively very close to those we get from the exercise described in the main body of the text.

[13]It should be easily recognized that tests of this nature do not necessarily have large power

measurement error in factor prices, we are unable to reject the null that the theory is right in a very large fraction of cases. With the standard deviation of measurement error assumed to be even just ten percent of w_{obs}, the success rate for the theory (i.e., the fraction of cases for consistent with the theory being true) is about ninety percent with the Capital I rental measure and a full hundered percent with the Capital II measure.

The robustness of our results were checked by performing the tests of (1.9) under various other configurations and data construction methods. These alternative configurations include,

(i) using different depreciation rates (3% and 10%) in calculating net capital stocks,

(ii) using gross capital stock (readily available from ISDB) instead of net capital stocks,

(iii) using the total (domestic + foreign) input-output matrix rather than domestic inputs matrix prescribed by Staiger (1986).

None of these variations changed the tests results greatly. The success rate for the theory was about the same as the results under the configuration we described earlier in the text (i.e., using net capital stock calculated using a five percent depreciation rate and with the I/O matrix simply reflecting the usage of domestic inputs as prescribed by Staiger (1986)).

against alternatives. Our results should then be viewed as only confirming the extent of *consistency* of the data with the theory.

1.5 Concluding Remarks

This paper has used OECD production and trade data to test the restrictions (derived by Helpman (1984)) on the factor content of trade flows which hold even under non-equalization of factor prices and in the *absence* of any assumptions regarding consumer preferences. Our results provide greater support for the theory than have many previous exercises: We are unable to reject the restrictions implied by the theory for the vast majority of country-pairs. Our results are quite robust to the factor price measures used and to a variety of assumptions made in the construction of necessary variables from observed data.

Table 1.1: Factor Prices

Factors	Category		US	CAN	KOR	DEN	FRA	GER	NET	UK
Labor (in US$)	Euro I	Production	13,059	12,592	1,638	13,137	14,141	17,151	17,423	12,327
		Non -Production	20,375	15,657	2,822	16,878	23,290	23,496	23,886	13,510
	Euro II	Production	13,059	12,592	1,638	13,333	14,715	18,789	18,177	12,595
		Managerial	26,589	21,165	7,189	24,985	40,855	34,011	36,670	21,011
		Clerical	14,869	11,460	2,910	17,313	16,221	16,389	18,363	9,323
		Others	21,578	16,960	2,495	15,788	22,859	24,544	25,083	14,529
Capital	Capital I		0.080	0.103	0.155	0.053	0.078	0.091	0.097	0.075
	Capital II		0.165	0.190	0.234	0.174	0.180	0.203	0.185	0.203

Notes: For Labor, the factor price figures presented in the Table above denote average annual compensation in US dollars to an employee of the designated type. For capital, the factor price denotes the rate of return. Rates of return were calculated as follows. Capital I Method: Operating Surplus / K and Capital II Method: (GDP - CE) / K where K denotes net capital stock, GDP gross domestic product and CE compensation to employees.

Table 1.2: Values of θ with Euro I and Capital I Method

	CAN	KOR	DEN	FRA	GER	NET	UK
USA	0.99	1.95	1.00	1.03	1.01	1.16	0.98
CAN		1.83	1.06	1.01	0.99	1.12	0.97
KOR			2.76	3.00	2.70	4.04	2.11
DEN				1.07	0.99	1.03	1.04
FRA					0.99	1.03	1.04
GER						1.01	0.97
NET							1.10

Table 1.3: Values of θ with Euro II and Capital I Method

	CAN	KOR	DEN	FRA	GER	NET	UK
USA	0.99	1.92	1.02	1.05	1.01	1.18	0.98
CAN		1.81	1.05	1.02	0.99	1.14	0.97
KOR			2.72	2.98	2.76	4.08	2.10
DEN				1.07	0.99	1.04	1.03
FRA					0.99	1.03	1.04
GER						1.00	0.97
NET							1.11

Table 1.4: Values of θ with Euro I and Capital II Method

	CAN	KOR	DEN	FRA	GER	NET	UK
USA	0.99	1.69	0.99	1.05	1.02	1.12	1.02
CAN		1.60	1.01	1.02	1.00	1.09	1.01
KOR			2.23	2.52	2.30	3.39	1.86
DEN				1.02	0.99	1.01	1.04
FRA					0.99	1.02	1.04
GER						0.99	0.99
NET							1.07

Table 1.5: Values of θ with Euro II and Capital II Method

	CAN	KOR	DEN	FRA	GER	NET	UK
USA	1.00	1.67	1.00	1.06	1.02	1.14	1.03
CAN		1.59	1.01	1.03	1.00	1.10	1.01
KOR			2.22	2.51	2.36	3.43	1.85
DEN				1.02	0.99	1.02	1.03
FRA					0.99	1.02	1.03
GER						0.99	0.99
NET							1.08

Table 1.6: Sign Test Results with Measurement Error Simulation

Euro I and Capital I

		Degree of Measurement Error		
		2.5%	5.0%	10.0%
Significance Level	1%	75.0%	82.1%	96.4%
	5%	75.0%	78.6%	92.9%

Euro II and Capital I

		Degree of Measurement Error		
		2.5%	5.0%	10.0%
Significance Level	1%	75.0%	85.7%	96.4%
	5%	75.0%	78.6%	89.3%

Euro I and Capital II

		Degree of Measurement Error		
		2.5%	5.0%	10.0%
Significance Level	1%	89.3%	96.4%	100.0%
	5%	82.1%	89.3%	100.0%

Euro II and Capital II

		Degree of Measurement Error		
		2.5%	5.0%	10.0%
Significance Level	1%	89.3%	96.4%	100.0%
	5%	85.7%	92.9%	100.0%

Chapter 2

Dynamic Comparative Advantage and R&D Spillover Effects among OECD Manufacturing Industries

2.1 Introduction

The role of research and development (R&D) activity as a primary determinant of long-run growth has been theoretically articulated and analyzed in a number of recent papers on endogenous growth theory (including in the well-known works of Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992)). In extending the framework of these endogenous growth models to an open-economy context, Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991) have also analyzed the role of international trade as a conduit of technology transfer and technological spillovers across countries and conversely the role of international technological spillovers on the pattern of comparative advantage and trade between nations. Specifically, they have shown that if technological knowledge could flow freely across national borders, the pattern of international trade will be determined by the relative factor endowments as predicted by the traditional Heckscher-Ohlin type factor proportions model of trade and that, in contrast, if technological spillovers across borders are unimportant, then comparative advantage itself may be endogenously determined (independently of factor endowment differences across countries). It follows, in latter case, that an active industrial policy in the form of R&D subsidies or tax incentives on R&D expenditures (even if only temporarily applied) could alter the comparative advantage of nations in production and even possibly allow technologically backward countries to catch up.[1] Temporary policies may thus permanently alter the course of economic history by generating dynamic comparative advantage in R&D intensive sectors.

Technological spillover across national borders is therefore a phenomenon of immense academic and policy interest and a prominent and growing empirical literature has recently attempted to estimate its extent. In a pioneering and widely-cited work, Coe and Helpman (1995) investigated the impact of domestic and foreign knowledge stocks on total factor productivity (TFP) using *aggregate*, i.e., national, data on R&D expenditure.[2] Their finding was that of significant technological spillovers across national borders – with foreign R&D proving an important determinant of improvements in domestic productivity.[3] A number of subsequent studies work-

[1] In the absence of such policies, the theory predicts that history (i.e., initial conditions) plays a dominant role in deciding the comparative advantage and the trade patterns: a country that begins with a head start in the accumulation of knowledge widens its productivity lead over time. See Chapter 7 and 8 in Grossman and Helpman (1991).

[2] Specifically, they used data on cumulative national R&D expenditures to proxy for domestic stocks of knowledge and data on stocks of R&D in foreign countries (weighted by the extent of bilateral trade) to proxy for foreign knowledge stocks.

[3] This work was preceded by a long and distinguished empirical literature examining the nexus between R&D activity and productivity performance in a closed-economy context (e.g., Terleckyj (1974), Scherer (1982), Griliches and Lichtenberg (1984) and Jaffe (1986), among others). Using firm level or industry level data mainly from the US, these studies usually found substantial R&D spillover effects across firms or industries within a country. See Nadiri (1993) and Griliches (1995) for excellent surveys.

ing with *aggregate* data (and a variety of methodological approaches) have also confirmed these results (See, for instance, Coe, Helpman and Hoffmaister (1997), Bernstein and Mohnen (1998) Eaton and Kortum (1999)).[4]

However, these aggregate level analyses are often criticized by many researchers because we observe substantial heterogeneity in the R&D intensities and the productivity performances across industries (e.g., Branstetter (1996) and Keller (1997)). To capture these industrial differences, more detailed analyses with disaggregated data are required. In addition, these findings of substantial international R&D spillovers in the previous literature do not sit well with the well-known results of Bern-joneBernard and Jones (1996a, 1996b) who, using data on a group of 14 OECD countries from the period 1970-1987, found that manufacturing industries (as opposed to economies in aggregate) showed little evidence of productivity convergence. Since most recent theories of economic growth predict that if there are significant technological spillovers, there should also be convergence in productivity across countries, and since we expect for spillovers to take place within largely manufacturing (on *a priori* grounds given the concentration of R&D in manufacturing), the finding of the former (i.e., spillovers) and the absence of the latter (i.e., convergence) constitutes somewhat of a puzzle.[5]

[4]In a nearly singular exception (to our knowledge), contrary results are reported by Branstetter (1996) who finds, using *firm level* patents data from the US and Japan, that technology spillover effects were mainly intra-national in scope and that while for Japanese firms, there is some weak evidence of positive benefit from US firms' R&D activity, there is *no* evidence of technological spillover from Japanese firms to US firms.

[5]Ironically, Bernard and Jones (1996a) found that it was other sectors, especially services, that drove *aggregate* convergence in productivity across OECD countries. This may be seen as surprising in itself since common intuition would suggest that it is in *manufacturing* sectors that spillovers would most likely take place. See Bernard and Jones (1996a) for a discussion.

It is this puzzle (broadly speaking) which this paper attempts to investigate. Since it is the manufacturing sector rather than the entire economy that we are concerned with, the use of disaggregated industry level data is called for and this is indeed what we employ. While the use of disaggregated industry level data in investigating international technological spillovers is itself not entirely new[6] (and indeed, has been attempted previously by Keller (1997)), our study departs from earlier work in one important respect: as we discuss in substantial detail later, we use recently published *country-specific* data from the OECD[7] on technology, inter-sectoral input-output relationships and bilateral trade that have never been used in this exercise before (including Keller (1997) who relied only on US input-output data (or Canadian patent data) to represent production linkages (or technology flows) for *all* sample countries instead).

Using disaggregated industry level data to estimate the relationship between TFP and domestic and foreign R&D capital stocks gives us the following results. In common with earlier work on this topic, we find first that domestic R&D activities (own-industry R&D and R&D spillovers from other domestic industries) are significant in explaining industrial productivity evolution. However, in strong contrast with Coe and Helpman (1995)'s findings on aggregate data, our analysis suggests that foreign countries' R&D activities had *little* positive impact on domestic manufacturing productivity. In the context of these findings, the non-convergence phenomenon in OECD manufacturing productivity reported by Bernard and Jones

[6]See Section 2.3 for brief description of previous literature.

[7]The data sources are the OECD Input-Output Database, OECD STAN Database, OECD Bilateral Trade Database and OECD ANBERD Database. See Appendix B.1 for more details.

(1996a, 1996b) seems less puzzling since the putative force driving convergence (i.e., technology spillovers through international trade) is itself found to be empirically unimportant.

The contribution attempted by this paper then is two-fold: it is the first study (to our knowledge) to use disaggregated *country-specific* data from a broad set of OECD countries to investigate the important question of technology spillover through international trade. Second, we believe that our findings of insignificant spillovers through trade resolve (at least partially) the puzzle regarding non-convergence of productivity in the OECD manufacturing sectors pointed to by Bernard and Jones (1996a, 1996b).

The resulting policy implications from our empirical findings are clear and strong. The importance of domestic technology externalities calls for appropriate industry policies such as R&D subsidies and tax incentives on R&D expenditures. In addition, the lack of international R&D spillovers may further justify the use of such policies in order to generate dynamic comparative advantage as was described in the beginning of this section.

The rest of the paper is organized as follows. Section 2.2 discusses the theoretical framework that motivates our empirical exercise. Section 2.3 describes the empirical methodology. Estimation results and robustness tests are presented in Section 2.4. Section 2.5 concludes. A detailed data appendix (Appendix B.1) describing data sources and construction is attached at the end.

2.2 Theory

The theoretical framework that motivates our empirical exercise derives directly from the well-known models of R&D-driven growth articulated by Romer (1990) and Grossman and Helpman (1991) and is quite similar to the framework adopted in the earlier empirical work of Coe and Helpman (1995) and Keller (1997).[8]

Here, the production function of industry i combines labor and horizontally differentiated intermediate goods in the standard Dixit-Stiglitz way and is given by:

$$Y_i = A_i L_i^{1-\alpha_i} \sum_{m=1}^{N_i} (x_{mi})^{\alpha_i}, \quad \text{where } 0 < \alpha_i < 1 \tag{2.1}$$

where Y_i denotes the final output of industry i, A_i denotes an exogenous technology factor, L_i denotes labor input, x_{mi} denotes the quantity of intermediate input of type-m employed in industry i's production process and N_i denotes the number of intermediate input available to industry i.

Following Romer (1990), we assume that technologies are embodied in capital services and that technological progress results from an expansion in the variety of specialized capital services available (i.e., by expanding N_i). Put another way, each intermediate variety is assumed to be produced by a specialized capital service according to some linear function. Then, the industrial production function above can then be rewritten as,

$$Y_i = A_i L_i^{1-\alpha_i} \sum_{m=1}^{N_i} (K_{mi})^{\alpha_i} \tag{2.2}$$

where K_{mi} denotes the specialized capital service of type-m which is used in industry i's production. This production function exhibits diminishing returns in each variety

[8] See also Barro and Sala-i-Martin (1995) and Aghion and Howitt (1998).

of the specialized capital services so that, in equilibrium, each industry uses all of the available varieties of specialized capital services in the same quantity by the symmetry. That is,

$$K_{mi} = \frac{K_i}{N_i} \tag{2.3}$$

Plugging equation (2.3) into the sectoral production function (2.2), we have

$$\begin{aligned} Y_i &= A_i L_i^{1-\alpha_i} \sum_{m=1}^{N_i} (\frac{K_i}{N_i})^{\alpha_i} \\ &= A_i L_i^{1-\alpha_i} K_i^{\alpha_i} N_i^{1-\alpha_i} \end{aligned} \tag{2.4}$$

Now, taking log on both sides and rearranging the terms, we have

$$\ln Y_i - (1-\alpha_i)\ln L_i - \alpha_i \ln K_i = \ln A_i + (1-\alpha_i)\ln N_i \tag{2.5}$$

The left-hand side of equation (2.5) is the familiar total factor productivity (TFP) level calculation formula in log terms.[9] Equation (2.5) implies that TFP level of industry i will be determined by some exogenous technology factor (A_i) and the number of varieties available to industry i (N_i). As we have already indicated, in this model, technological progress takes place through R&D expenditures (or via increase in cumulative R&D capital stock) that raise N_i over time.

Having defined TFP, we can rewrite equation (2.5) in a more compact way. Adding a country subscript, j, we have,

$$tfp_{ij} = a_{ij} + (1-\alpha_{ij})n_{ij} \tag{2.6}$$

[9]Here, the varieties of the intermediate good, the x_{mi}, are assumed to be produced by monopolists while the market structure of final output is competitive. Note that despite the monopoly pricing of the intermediate inputs, the usual Solow residual correctly measures the contributions to productivity from exogenous technology factor ($\ln A_i$) and expansion of varieties ($\ln N_i$). See Barro (1998) for descriptions of growth accounting under various model specifications.

where tfp_{ij} denotes log of TFP level, $a_{ij} \equiv \ln A_{ij}$ and $n_{ij} \equiv \ln N_{ij}$.

With aggregate data as in Coe and Helpman (1995), there are only two sources of relevant R&D capital stock which can affect n_{ij}: aggregate domestic and aggregate foreign R&D capital stocks. However, given the disaggregated level of our analysis, we can separate at least four types of R&D capital stock which can influence an industry's TFP level. They are: (i) industry's own R&D capital stock, (ii) other industries' R&D capital stocks in the same country, (iii) same industry's R&D capital stock in its trading partner countries and (iv) other industries' R&D capital stocks in its trading partner countries. Formally,

$$n_{ij} = G(R_{ij}, \{R_{kj}\}_{k\neq i}^{p}, \{R_{il}\}_{l\neq j}^{q}, \{\{R_{kl}\}_{k\neq i}^{p}\}_{l\neq j}^{q}) \tag{2.7}$$

where R is cumulative R&D capital stock and the first and the second subscripts to R denote industries (i and $k = 1, \cdots, p$) and countries (j and $l = 1, \cdots, q$), respectively. Each argument in G corresponds to the descriptions in (i)–(iv) above.

2.3 Empirical Framework

2.3.1 Measurement Methodology

Equation (2.7) above postulates that the overall R&D measure impacting the production function, n_{ij}, is itself determined by own industry domestic and foreign R&D stocks, and other-industry domestic and foreign R&D stocks. However, the theory does not specify *exactly* how these determine n_{ij} in a manner that is empirically implementable. A simple aggregation of R&D stocks is clearly inappropriate, since, for instance, we would not expect domestic own-industry R&D to determine n_{ij} to the same extent as does, say, foreign other-industry R&D. How then should we use data on international R&D stocks to determine n_{ij}?

Much energy has been devoted in the literature to addressing this question. As Griliches (1995) has noted in his magisterial survey on this topic, each industry in this framework "borrows" different amounts of knowledge from each other according to the "economic and technological distance" between them and "the relevant concept of *distance* is very hard to define empirically." From the stand point of any one industry, other industries will have to be weighted suitably, with weights indicating the effective fraction of knowledge that this industry borrows from each of the rest . But, what is such a weighting function to be based upon? The literature has suggested several approaches which we discuss here briefly before moving on to a more detailed discussion of the methodology that we ourselves adopt.

First, a broad class of empirical work in this area has attempted to measure the "intellectual-scientific" proximity of industries by using patent data – an idea first implemented by Scherer (1982) and subsequently developed in a variety of ways in the prominent studies of Griliches and Lichtenberg (1984) and Jaffe (1986) *inter alia* that followed. The presumption of this approach is that patent data, such as data on the industry where the invention occurred and the industries where the patent was expected to have its major impact, or alternatively data on similarity in distribution of patents by patent classification, provides information on the technological distance between industries and can therefore be used to construct the relevant weights. Thus, by analyzing firm level patents data, technological proximity or distance among related firms or industries is measured. However, the complexity of these methods and the data requirements inherent in their implementation imply that studies of this nature can only be conducted on countries for which detailed data on patents is available. This effectively renders infeasible broad studies on *international* R&D spillover effects.[10]

An alternative approach is the *input-output* approach – first taken by Terleckyj (1974) who analyzed domestic R&D spillover effects at the industry level in a closed economy context (using data on US industries). Specifically, he used the intermediate input purchase matrix to calculate effective outside R&D capital stocks under the assumption that the contribution of other industries' R&D capital stock is measured by the extent of purchases of intermediate goods from those industries. The natural and consistent extension of this methodology into open economy context where international R&D spillovers may exist, was using bilateral import shares as a weighting scheme for foreign R&D capital stock – as implemented by Coe and Helpman (1995) in their study using *aggregate* data on R&D stocks.[11]

Other researches have combined both approaches. Thus, Keller (1997), in a paper with country and industry coverage similar to ours, used the so-called "Yale technology matrix" based on Canadian patents data for the year 1978-1987 to deter-

[10]If one were willing to limit oneself to a narrow context (in terms of country and industry coverage), this approach is still feasible: Branstetter (1996) constructed technology proximity indices using patent data from around 200 Japanese and US firms' in selected industries with high R&D intensities and used these as a weighting scheme. As we had already mentioned in Section I, he found virtually no evidence of international R&D spillover effects.

[11]Keller (1998) has criticized the inferences made by Coe and Helpman (1995) that trade acts as a conduit for international technology spillovers by showing that randomly generated trade shares could lead to similar or even higher international spillover effects on productivity growth compared actual trade shares. However, Coe and Hoffmaister (1999) have responded to Keller (1998) by showing that Keller's 'random' weights were not truly random but rather simple averages with a random error. They have proposed other ways to generate truly random weights and showed that randomly created trade patterns in this way did not give rise to positive international R&D spillovers.

mine the weights of domestic R&D stocks in different industries and used bilateral import shares to calculate the weights of foreign R&D capital stock.[12]

Each of these approaches has its own limitations.[13] For example, in the approaches using patent data, the value of all patents is often assumed to be equal and only the number of registered patents is assumed to matter. Since each patent has different value in generating productivity progress and not all innovations are registered, these are unrealistic assumptions. The input-output approach is also criticized by many researchers on the grounds that pure knowledge could spill over across industries and countries without any purchase of intermediate goods.[14]

Be these differences as they may, it is ultimately data availability that dictates our choice of methodology. Since internationally comparable data at a disaggregated level is available only on technology and input-output linkages in production (and this too only recently from the OECD, as we have already mentioned), it is the *input-output* approach that we employ in this paper. This data permits us to split even the manufacturing sector in thirteen different industries, and so we are able to

[12]While deserving of praise for making best use of the available data, this method is susceptible to several criticisms. First, applying one country's technology matrix to all countries in the sample is not adequate, because it neglects potentially different inter-industry technology flows structure between countries. It is hard to imagine that the national patents structures between, for example, Japan and Canada are identical. Second, the use of this technology matrix to represent inter-industry technology relationships within a country and use bilateral import shares instead to weight foreign R&D stocks opens up the methodology to the charge of inconsistency.

[13]See Nadiri (1993) for a discussion of the merits and demerits of each approach.

[14]It is perhaps worth noting that the discrepancy between results using the technology matrix derived using patents data and the input-output matrix instead was argued to be not terribly severe by de la Potterie and van Pottelsberghe (1996). He examined correlations between the weighting coefficients constructed by using Scherer (1982)'s technology flow matrix and by using US 1972 input-output matrix instead and found them to be very high: 0.87 for all sectors and 0.92 for the core sectors - chemicals, machinery, mechanical engineering, instruments, electrical engineering and electronics.

conduct the analysis at the high level of disaggregation necessary for addressing the puzzle posed by Bernard and Jones (1996a, 1996b)'s findings we have mentioned earlier.

Given our data on input-output linkages in each country[15] and given data on industrial bilateral trade flows, the construction of the *effective* level of outside R&D capital stocks, following the input-output methodology, is straightforward as was also adopted by Coe and Helpman (1995) and Keller (1997). First, we assume that the effective own R&D capital stock of industry i in country j, denoted by RD_{ij}, is simply its actual R&D capital stock:

$$RD_{ij} = R_{ij} \tag{2.8}$$

Now, let d_{kij} be the (k, i) element of country j's domestic input-output matrix representing the amount of intermediate and investment goods purchased by industry i from industry k. Then, the domestic inter-industry weighting coefficients in country j can be calculated as

$$\omega_{kij} = \frac{d_{kij}}{\sum_{k\neq i}^{p} d_{kij}} \quad \text{where} \quad \sum_{k\neq i}^{p} \omega_{kij} = 1$$

For industry i, the effective R&D capital stock from other domestic industries $(\overline{RD}_{ij})$ is then constructed by

$$\overline{RD}_{ij} = \sum_{k\neq i}^{p} \omega_{kij} R_{kj} \tag{2.9}$$

Now, the weighting coefficients for foreign R&D capital stock in the same industry is the industrial bilateral import share of each country. Thus, let ν_{ijl} denote

[15] The input-output data used in this paper is the sum of the intermediate goods flow matrix and the investment flow matrix. See data appendix for more detail.

country l's share of imports of good i by country j so that $\sum_{l \neq j}^{q} \nu_{ijl} = 1$, then the industry i's effective R&D capital stock from the same industry in its trading partner countries (RF_{ij}) can be calculated as

$$RF_{ij} = \sum_{l \neq j}^{q} \nu_{ijl} R_{il} \tag{2.10}$$

Similarly, using the import input-output matrix[16] of country j with typical element m_{kij}, we can construct weighting coefficients:

$$\mu_{kij} = \frac{m_{kij}}{\sum_{k \neq i}^{p} m_{kij}} \quad \text{where} \quad \sum_{k \neq i}^{p} \mu_{kij} = 1$$

so that for industry i in country j, the effective R&D capital stock from other industries in its trading partners ($\overline{RF}_{ij}$) is constructed by

$$\overline{RF}_{ij} = \sum_{k \neq i}^{p} \mu_{kij} RF_{kj} \tag{2.11}$$

With the relevant variables calculated in these ways, we now turn to the empirical specifications.

2.3.2 Empirical Model

Combining equations (2.6)-(2.11) described above, our basic empirical specification takes the following log-linear form:space0.1in

$$tfp_{ijt} = \beta_0 + \beta_1 rd_{ijt} + \beta_2 \overline{rd}_{ijt} + \beta_3 rf_{ijt} + \beta_4 \overline{rf}_{ijt} + \eta_{kjt}$$

where lower case variables represent log of the corresponding effective R&D capital stock variables as defined in the previous subsection and t is time subscript. We

[16] This is also the sum of imported intermediate goods flows matrix and imported investment goods flows matrix.

allow the error term in the above equation to contain an industry-country-specific component such that

$$\eta_{ijt} = \theta_{ij} + \epsilon_{ijt}$$

where ϵ_{ijt} is assumed to be a normal *iid* disturbances. If θ_{ij} is uncorrelated with the right hand side regressors, then we can proceed to estimate the model using the random effects framework. As pointed out by Griliches (1995) and Barro (1998), however, this industry-country-specific component in the error term may be correlated with the industry's own R&D expenditure level: the productivity level is specified to depend on R&D capital stock, while R&D, in turn, may depend on the level of output or on the expectation of future output. In this case, estimates are biased unless we correct for the correlation between the industry-country-specific effects and domestic R&D level. To minimize the issue of simultaneity, we estimate the model using a fixed effects estimator by allowing the industry-country-specific dummies to absorb part of the error that is correlated with the regressors.[17] Then, our final estimation equation is:

$$tfp_{ijt} = \theta_{ij} + \beta_1 rd_{ijt} + \beta_2 \overline{rd}_{ijt} + \beta_3 rf_{ijt} + \beta_4 \overline{rf}_{ijt} + \epsilon_{ijt} \tag{2.12}$$

where θ_{ij} is an industry-country-specific fixed effect.

Another econometric issue, given the cross-sectional and the time series dimensions of our data ($N = 104$ with 8 countries and 13 industries and $T = 15$ years), is the possibility that two or more variables are trended and contain unit roots –

[17]The standard alternative would be, of course, the instrumental variable approach. However, as the literature has pointed out, data on variables that may reasonably be used as instruments (such as the real factor prices of R&D input or government policies with respect to R&D) are not available and thus the technique of instrumental variable estimation is generally infeasible.

rendering the regression results spurious. We, therefore, submit our data to the panel unit root test developed by Levin and Lin (1993).[18] We conducted two types of panel unit root tests: one with individual-specific fixed effects in the model and the other with both individual-specific fixed effects and a time trend. The results are shown in Table 2.1. When only individual-specific fixed effects are included (the first column in Table 2.1), one variable ($\overline{rd}$: effective R&D capital stock of other industries in the same country) in our panel data appears to have a unit root. However, when the time trend is additionally included (second column in Table 2.2), the panel unit root hypothesis was strongly rejected for all variables.[19] Confirming that the regression results of equation (2.12) are unlikely to be spurious in the panel context, we now turn to the estimation results.

2.4 Estimation Results

Our data sample consists of 8 OECD countries with 13 manufacturing industries for the period 1973-1987, which amounts to 1,560 observations.[20] We start by reporting results from our benchmark specification: estimation of (2.12) with industry-

[18]There are two versions of Levin and Lin's panel unit root tests. Levin and Lin (1992) constrains the dynamics of the augmented Dickey-Fuller to be the same across individuals while Levin and Lin (1993) allows the dynamics to differ across individuals. We conducted the panel unit root test following their 1993 paper.

[19]Note that this result is significantly different from that with the aggregate data in Coe and Helpman (1995). In their paper, their panel unit root tests confirm that the variables are non-stationary so that they estimate their equations on panel data and interpret the results as pooled cointegrating equations.

[20]The new OECD publications allowed us to contruct the data for the period 1973-1991. However, we report the estimation results for the period 1973-1987 in this paper in order to match the time period in Bernard and Jones (1996a, 1996b) study (1970-1987) as close as possible (unfortunately though, R&D data for years earlier than 1973 is not available in our data). The unreported estimation results with our entire sample period do not change our conclusions both quantitatively and qualitatively.

country-specific fixed effects. To demonstrate robustness, we subsequently present results from the estimations of several additional specifications (which include time-specific fixed effects, time-lags on the foreign R&D variables and growth rate regressions).

2.4.1 Benchmark Case

OLS estimates of (2.12) with White's heteroscedasticity-consistent standard errors are presented in Table 2.2 in which the regressors are introduced sequentially. Column (i) of the table provides estimation results with only own R&D capital stock (rd) included as a regressor. The elasticity of TFP with respect to its own R&D is 0.394 and is precisely estimated at the 1% level. By adding the weighted R&D capital stock of other industries in the same country ($\overline{rd}$) on the right hand side, $\hat{\beta}_1$ is substantially reduced to 0.096 and $\hat{\beta}_2$ is estimated to be 0.358, both being significantly different from zero at the 1% significance level. We note first that β_2 is the elasticity of industrial TFP with respect to the 'weighted sum' of domestic-outside R&D capital stock. Thus, β_2 is to be interpreted as the percentage change in industry i's TFP when the *effective* R&D capital stocks of *all other* domestic sectors increase by 1%. To get the elasticity of i industry's TFP with respect to k industry's *actual* R&D capital stock, the estimated β_2 needs to be multiplied by

$$\frac{\omega_{kij} R_{kj}}{\sum_{k \neq i}^{p} \omega_{kij} R_{kj}} \tag{2.13}$$

where ω is the domestic inter-industry weighting coefficients defined in section 3.1.[21] Thus, it should not be seen as surprising that $\hat{\beta}_1$ is smaller than $\hat{\beta}_2$.[22]

Column (iv) in Table 2.2 presents the estimation results with the full specification of (2.12). The elasticities of industrial TFP with respect to both domestic R&D capital stocks (β_1 and β_2) do not change much and are still precisely estimated at 1% and 5% significance level, respectively. What is interesting, however, is the estimated coefficients on our primary variables of interest: R&D stocks abroad (in the same industry and otherwise) do not seem to have any significant effect on domestic industry's TFP. The estimates of both coefficients on foreign R&D capital stocks (own industry foreign R&D and other industry foreign R &D: β_3 and β_4 respectively), are indistinguishable from zero at any standard confidence level and the sign of β_4 is even negative although it is insignificant. Thus, using industry level data, we see no evidence of international technology spillovers in our benchmark specification – a result that stands in stark contrast to those obtained by Coe and Helpman (1995) who found the elasticity with respect to foreign R&D capital stock to be positive (albeit smaller than that of domestic R&D in magnitude).

Another thing to note is the changes in goodness of fit represented by R^2 (or adjusted R^2) when we are moving from column (i) to (iv). By adding domestic other industries' R&D capital stock (column (ii)), both R^2 and adjusted R^2 increase by almost 10%. But after that, the improvements in the goodness of fit of the

[21] See Appendix B.2 for derivation of (2.13)

[22] The average value of (2.13) in our sample is 0.062. This implies that on average, the elasticity of i industry's TFP with respect to k industry's actual R&D capital stock is 0.015 ($= 0.240 \cdot 0.062$).

model are essentially negligible when foreign R&D capital stock variables are added (only by 0.4% and 0.1%, respectively). This confirms again that the lion's share of the variation in industrial total factor productivity is explained by domestic R&D activities, not by foreign R&D capital stocks.

2.4.2 Time-specific Fixed Effects

Table 2.3 reports the estimation results of the model including additional time dummies in (2.12). These time dummies are introduced in an attempt to control for any global shock that may be common across industries. Although they are not reported here, the estimated time fixed effects are not significant in most cases which may be the reason why the R^2 and the adjusted R^2 are not improved that much after adding the time dummies.[23] One notable change in the estimation results is that the estimated domestic R&D spillover effects (β_2's) decrease substantially compared to the ones in Table 2.2 where no time specific effects were added in the model. This implies that the pattern of domestic R&D spillovers has been changed over time (although time dummies are themselves insignificant).

Other than these, the estimation with additional time-specific effects confirms the results of our benchmark case: both own R&D capital stock and domestic R&D spillovers appear important in explaining industrial TFP evolution, while R&D activities in the foreign trading partners appear to have little positive impact on domestic industry TFP.

[23]On the other hand, the industry specific fixed effects are statistically significant in two thirds of the cases.

2.4.3 Time Lags on Foreign R&D Capital Stocks

The literature has often suggested that foreign R&D capital stock may take longer time to impact domestic TFP than domestic R&D stocks. We therefore also implement the regression with lagged foreign R&D capital stock variables. Specifically, we assume that domestic R&D capital stocks have contemporaneous effects on domestic TFP level and impose (alternatively) one-year and two-year time lags on foreign R&D capital stock variables. These results are presented in Table 2.4.

As before, the first column shows regression results only with industry-country-specific fixed effects and the second column lists estimates with time-specific fixed effects added. Notice that by allowing time lags the goodness of fit has been improved substantially (by more than 10%) and all the coefficients are positive when the lag on foreign R&D capital stock is one year. Thus, the upper panel of Table 2.4 with one-year lag on foreign variables is the most favorable model. But even in this case, both foreign R&D capital stocks appear to be statistically insignificant at any standard confidence level: The results with benchmark case seem to be robust to the different lag structures on foreign R&D capital stock.

2.4.4 Regressions in Growth Rates

Another different specification we considered used growth rates rather than levels of variables. The regression in growth rates was implemented using the following specification:

$$\frac{\Delta TFP_{ijt}}{TFP_{ijt}} = \lambda_0 + \gamma_1 \frac{\Delta RD_{ijt}}{RD_{ijt}} + \gamma_2 \frac{\Delta \overline{RD}_{ijt}}{\overline{RD}_{ijt}} + \gamma_3 \frac{\Delta RF_{ijt}}{RF_{ijt}} + \gamma_4 \frac{\Delta \overline{RF}_{ijt}}{\overline{RF}_{ijt}} + \epsilon_{ijt} \quad (2.14)$$

where Δ denotes the first difference of the subsequent variable.

Table 2.5 presents the regression results of equation (2.14) with no lags and one-year lag on foreign R&D capital stock.[24] Although R^2's and adjusted R^2's are reduced substantially when compared with the log level regressions, the main implications remain the same: the domestic R&D capital stocks are always significant and the foreign R&D capital stocks remain insignificant in explaining the variation of the industrial total factor productivity.

Starting with the benchmark case with industry-country-specific fixed effects, we estimated the model with a variety of specification to see if our results are robust. Overall, these results lead us to conclude that the domestic R&D activities are significantly correlated with the domestic TFP while foreign R&D capital stocks have little impact on the industrial productivity.

2.5 Concluding Remarks

This paper has attempted to investigate the extent of international technology spillovers among OECD manufacturing industries through international trade – a channel that has received substantial emphasis in the theoretical and policy literature. However, our analysis of the data yields negative results. While industrial productivity appears to be significantly related to domestic R&D activities (both in the same industry as well as from other industries), foreign R&D spillover effects appear to be statistically insignificant in these OECD manufacturing industries.

The results of our industry level analysis stand in contrast to those obtained

[24] We also estimated model with two-year lags on foreign R&D capital stocks. But the F-statistics of this specification reveals that the significance of the model itself (i.e., the joint test of the significance of all variables in the model) is rejected at any standard significance level and thus we do not report this specification here.

by Coe and Helpman (1995) who reported positive results for international R&D spillover effects with aggregate level data. Since we used the data from only manufacturing industries, direct comparison with their findings may not be possible and hence more comprehensive data analysis including non-manufacturing industries is required. On the other hand, our results may help explain the empirical findings of Bernard and Jones (1996a, 1996b) as to the non-convergence of productivity in OECD manufacturing (since non-convergence across countries is perhaps not surprising if international R&D spillovers are unimportant).

The policy implications of our empirical findings are strong and clear. The importance of domestic technology externalities calls for appropriate industry policies such as R&D subsidies and tax incentives on R&D expenditures. In addition, the lack of international R&D spillovers may further justify the use of such policies in order to generate dynamic comparative advantage.

It is perhaps worth emphasizing that, while we have investigated here a channel for technology spillovers that has been emphasized substantially in the literature (i.e., international trade), we have ignored several other channels which have been hypothesized as well. Enhanced understanding of R&D spillover effects is likely to be achieved by detailed empirical investigation of these channels, most notably through foreign direct investment. We leave this as a topic for future research.

Table 2.1: Panel Unit Root Test (1973 - 1987)

variables	Levin and Lin (1993) Test Statistics	
	Model 1 (without time trend)	Model 2 (with time trend)
tfp	-4.37	-8.34
rd	-5.26	-10.12
$\overline{rd}$	-0.12	-5.32
rf	-7.54	-9.23
$\overline{rf}$	-8.31	-9.97

Note: The critical values at 1%, 5% and 10% confidence levels are -2.58, -1.96 and -1.64, respectively. The underlying models are in equation (1) of Levin and Lin (1993) which are given by

Model 1: $\Delta y_{it} = \alpha_i + \delta_i y_{it-1} + \sum_{L=1}^{p_i} \delta_{iL} \Delta y_{it-L} + \epsilon_{it}$

Model 2: $\Delta y_{it} = \alpha_{i1} + \alpha_{i2} t + \delta_i y_{it-1} + \sum_{L=1}^{p_i} \delta_{iL} \Delta y_{it-L} + \epsilon_{it}$

All variables are in logarithm and the definitions of the variables are as follows:
tfp: total factor productivity
rd: own industry's effective R&D capital stock
$\overline{rd}$: other industries' effective R&D capital stock in the same country
rf: same industry's effective R&D capital stock in the trading partner countries
$\overline{rf}$: other industries' effective R&D capital stock in the trading partner countries

Table 2.2: TFP Regression with Industry-Country-Specific Fixed Effects

coefficients	(i)	(ii)	(iii)	(iv)
β_1	0.394*** (0.017)	0.096*** (0.025)	0.102*** (0.026)	0.083*** (0.025)
β_2		0.358*** (0.137)	0.294** (0.148)	0.240** (0.115)
β_3			0.093 (0.076)	0.058 (0.042)
β_4				−0.017 (0.021)
F	56.45	64.23	63.83	63.22
R^2	0.465	0.543	0.547	0.548
R^2-adjusted	0.457	0.535	0.538	0.539

Note: The dependent variable is log of industrial total factor productivity. Heteroscedasticity-consistent standard errors are in parentheses. All equations include unreported, industry-country-specific constants. *, ** and *** represent estimates are significant at 10%, 5% and 1% confidence level, respectively.

Table 2.3: TFP Regression with Industry-Country-Specific and Time-Specific Fixed Effects

coefficients	(i)	(ii)	(iii)	(iv)
β_1	0.117*** (0.023)	0.089*** (0.026)	0.094*** (0.024)	0.095*** (0.026)
β_2		0.155*** (0.059)	0.170** (0.072)	0.198** (0.085)
β_3			0.066 (0.053)	0.061 (0.051)
β_4				−0.090 (0.079)
F	58.79	58.98	58.63	58.44
R^2	0.571	0.592	0.593	0.595
R^2-adjusted	0.561	0.582	0.583	0.585

Note: The dependent variable is log of industrial total factor productivity. Heteroscedasticity-consistent standard errors are in parentheses. All equations include unreported, industry-country-specific constants. *, ** and *** represent estimates are significant at 10%, 5% and 1% confidence level, respectively.

Table 2.4: TFP Regression with Different Lag Structures on Foreign R&D Capital Stock

coefficients	Individual Fixed Effects	Individual and Time Fixed Effects
One-Year Lag		
β_1	0.102*** (0.027)	0.095*** (0.024)
β_2	0.231** (0.110)	0.183** (0.072)
β_3	0.096 (0.087)	0.080 (0.076)
β_4	0.081 (0.092)	0.054 (0.051)
F	70.96	65.15
R^2	0.691	0.698
R^2-adjusted	0.684	0.686
Two-Years Lag		
β_1	0.076*** (0.017)	0.075** (0.017)
β_2	0.313* (0.183)	0.164* (0.093)
β_3	−0.007 (0.022)	−0.031 (0.023)
β_4	0.006 (0.034)	−0.139 (0.465)
F	76.57	82.79
R^2	0.611	0.623
R^2-adjusted	0.600	0.612

Note: The dependent variable is log of industrial total factor productivity. Heteroscedasticity-consistent standard errors are in parentheses. All equations include unreported, industry-country-specific and time-specific constants. *, ** and *** represent estimates are significant at 10%, 5% and 1% confidence level, respectively.

Table 2.5: TFP Growth Rate Regression

coefficients	Lags on Foreign R&D Capital Stock: No Lags	One-Year Lag
γ_1	0.060* (0.034)	0.102** (0.045)
γ_2	0.320* (0.193)	0.191* (0.108)
γ_3	0.018 (0.027)	0.016 (0.021)
γ_4	0.072 (0.044)	0.024 (0.045)
F	19.28	19.02
R^2	0.239	0.312
R^2-adjusted	0.209	0.211

Note: The dependent variable is log of industrial total factor productivity. Heteroscedasticity-consistent standard errors are in parentheses. All equations include unreported constants. *, ** and *** represent estimates are significant at 10%, 5% and 1% confidence level, respectively.

Chapter 3

Import Competition and Rate of Return to Capital in US Manufacturing Industries

3.1 Introduction

The theoretical literature in international trade has provided a rich and varied analysis of the impact of changes in goods prices on factor rewards. Thus, for instance, in the Heckscher-Ohlin model of trade, where factors of production are assumed to be fully mobile across sectors, a reduction in the domestic price of the importable good is predicted to result in a reduction (improvement) in the reward to capital if capital is the factor of production used intensively in the production of the importable (exportable) good. In contrast, the Specific-Factors model of trade, where sectoral specificity of (some) factors is assumed, a reduction in the price of the importable is predicted to result in a reduction in reward to factors that are specific to the production of the importable sector.

Despite this rich range of theoretical predictions, empirical investigations of the relation between import competition and the rate of return to capital are surprisingly rare. One major exception is the work of Grossman and Levinsohn (1989) (G&L

hereafter),[1] who built on an empirical framework pioneered by Pakes (1981, 1985),[2] to look at the effects of changes in import prices on the stock market rate of return to capital in six US manufacturing industries for the 1975-1986 time period. G&L found that import competition had economically and statistically significant effect on the rate of return to capital in five out of six industries. Further, the magnitudes of their estimated coefficients suggest that the industrial capital stocks are almost perfectly immobile across industries: thus, their empirical findings gave support to the Specific-Factors model.

This study extends the G&L analysis in two ways. First, in contrast to G&L's use of data on merely six industries, we consider a much broader set of sectors: Our data set includes comprehensive panel data on twenty two industries comprising over eight hundred firms. Beyond providing a more comprehensive coverage, data on a broader set of industries also allows us to exploit variation in the import penetration ratio (which serves as a tentative proxy for the degree of import competition) and the industry import price index. Second, we extend the data in the time dimension as well: Our data stretches from 1974 to the year 1992.

We find that unanticipated changes in import prices have statistically significant effects on the excess rate of return to capital in the import-competing industries. The hypothesis of perfect capital mobility across industries, as postulated in the Heckscher-Ohlin model of international trade, is thus rejected by the data. At the

[1] The only other work on this issue, to our knowledge, is that of Brander (1991) whose event-study examined the stock market impact of the US-Canada free trade agreement in the year of 1988.

[2] In these papers, Pakes developed the empirical framework to study the relationship between R&D expenditures, patent applications and the (excess) stock market return on firms' equity.

same time, the size of the estimated coefficients indicate that the stock market capital is not entirely industry-specific, in contrast to assumptions made in the Specific-Factors model of trade (unlike G&L's results). Our results suggest that estimation of the impact of trade policy changes or other changes in the external environment on factor prices need to be based on models which allow for intermediate degrees of factor mobility.

The rest of this paper proceeds as follows. Section 3.2 describes the theoretical framework that underlies the empirical exercise. Section 3.3 details the econometric model and discusses estimation issues. Section 3.4 presents our estimation results. Section 3.5 concludes.

3.2 Theory

The theoretical approach in this paper follows G&L which, in turn, adopted the methodology developed by Pakes (1981, 1985). We consider a small open economy where the industrial import prices are exogenously given and each domestic firm i in industry j shares a common constant returns to scale technology. We assume that at the beginning of each time period, management chooses an investment program of capital (which involves convex adjustment cost function) to maximize the expected discounted value of the current and future net cash flows from the firm's investment activities. Non-capital inputs (such as labor and energy) are assumed to be adjusted costlessly at the beginning of each period to maximize the profits attainable in that period.

Management's evaluation of a given program is found by substituting that program into the net cash flow function, taking the expectation of the discounted value of future net cash flows plus current profits conditional on management's current information set (Ω_t) and subtracting the current cost of the investment program ($\bar{I}_t$) from this expectation. Formally, the value of the investment program of firm i in industry j at time t can be written as

$$V(\Omega_t, \bar{I}_t) = H(\bar{I}_t, I_{t-1}, I_{t-2}, \ldots, Z_t) - \bar{I}_t \tag{3.1}$$

where the firm and the industry indices are dropped for simplicity. The current information set available to management (Ω_t) at the time various input decisions are made includes the past investment expenditures of the firm (I_s for $s < t$) and other information variables (Z_t). The information on the distribution of future net cash flows will be provided by Ω_t. $H(\cdot)$ provides the expected discounted value of future net cash flows and current profits conditional on current information available to the firm's management.

As assumed, at the beginning of each period, management will maximize $V(\cdot)$ with respect to $\bar{I}_t$ so that at the optimal value of I_t,

$$V^*(\Omega_t) = \max_{\bar{I}_t} V(\Omega_t, \bar{I}_t) = H(I_t, I_{t-1}, I_{t-2}, \ldots, Z_t) - I_t \tag{3.2}$$

will hold, where $V^*(\Omega_t)$ is management's evaluation of the firm conditional on optimal investment behavior.

Now, if the stock market provided an exact evaluation of the expected discounted value of the firm's future net cash flows conditional on the same information used by management, then the one-period excess rate of return on the firm's equity in period t over the return expected at the beginning of the period ($r_t - E_{t-1}(r_t)$, where r_t is the stock market return in period t and E_t is the statistical expectations operator conditional on time t information) would be equal to the percentage increase in the expected discounted value of these net cash flows *caused by the information that accumulated over the given period.* Put another way, only unexpected change in the value of the investment program will affect the excess return on firm's equity. Using logarithm, this implies that [3]

$$r_t - E_{t-1}(r_t) = \ln V_t^*(\Omega_t) - E_{t-1}(\ln V_t^*(\Omega_t)) \tag{3.3}$$

Equation (3.2) and (3.3) are two fundamental equations to derive the empirical specifications below. For estimation purposes, we must impose a functional restriction on $H(\cdot)$ in equation (3.2). We assume the following log linear form:

$$H(\cdot) = Z_t \prod_{\tau=0}^{\infty} I_{t-\tau}^{\lambda_\tau} \tag{3.4}$$

where λ_τ represents the weighting coefficient of the contribution of the current and the past capital investment activities to the current and the future net cash flows.

Now by plugging equation (3.4) into equation (3.2), we can explicitly solve the maximization problem for the optimal current period investment level (I_t). Then, by putting back this solution into equation (3.2), we find

$$V_t^*(\Omega_t) = \frac{1-\lambda_0}{\lambda_0} Z_t^{\frac{1}{1-\lambda_0}} \left(\lambda_0 \prod_{\tau=1}^{\infty} I_{t-\tau}^{\lambda_\tau}\right)^{\frac{1}{1-\lambda_0}} \tag{3.5}$$

Note that the only stochastic variable in $V_t^*(\Omega_t)$ is now Z_t (since the past investment activities are already known to management and stock market participants). Then,

[3]Equation (3.3) is the discrete-time approximation of continuous time results. For the derivation of continuous time-version, see Pakes (1981).

by plugging equation (3.5) into equation (3.3), we find the relationship between the excess return and the unexpected shock to the information variable as follows:

$$r_t - E_{t-1}(r_t) = \frac{1}{1-\lambda_0}(\ln Z_t - E_{t-1}(\ln Z_t)) \tag{3.6}$$

This result can be applied both to the individual firm's equity and to the portfolio of stocks that comprises all equities in the stock market as a whole. Then, the excess returns on the individual stock and on the market portfolio can be written as

$$r_{ijt} - E_{t-1}(r_{ijt}) = \theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) \tag{3.7}$$

$$r_{mt} - E_{t-1}(r_{mt}) = \theta_m(z_{mt} - E_{t-1}(z_{mt})) \tag{3.8}$$

respectively, where subscripts i, j and t are the indices for firm, industry and time and subscript m denotes market portfolio. r_{mt} is the realized 'average' stock market rate of return to all industries in the portfolio and z_{mt} collects the variables that affect 'average' firm's profits. θ_{ij} is defined by $\frac{1}{1-\lambda_0}$ and θ_m is the portfolio-weighted average of individual θ_{ij}'s. Equation (3.7) and (3.8) imply that the excess rate of return to ('average') firm's equity at time t depends on the unexpected changes of the information variables that affect ('average') firm's current and future profits.

The final step in this section is to combine equations (3.7) and (3.8) by introducing two types of behavioral assumptions on the stock market investors (See G&L). The first and simplest case is to assume risk-neutral stock market investors. In this case, the arbitrage condition ensures that

$$E_{t-1}(r_{ijt}) = E_{t-1}(r_{mt}) \tag{3.9}$$

This arbitrage condition implies the following definition of the excess rate of return to capital with risk neutrality assumption:

$$ER^N_{ijt} \equiv r_{ijt} - r_{mt}$$

That is, the excess rate of return is defined by the deviations of the realized rate of return on stock i from the realized return on the market portfolio. Plugging equation (3.7) and (3.8), we have

$$\begin{aligned} ER^N_{ijt} &\equiv r_{ijt} - r_{mt} \\ &= \theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) - \theta_m(z_{mt} - E_{t-1}(z_{mt})) + \{E_{t-1}(r_{ijt}) - E_{t-1}(r_{mt})\} \\ &= \theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) - \theta_m(z_{mt} - E_{t-1}(z_{mt})) \end{aligned} \tag{3.10}$$

where we used equation (3.9) to derive the last equality above. Equation (3.10) implies that the excess rate of return on stock i (defined by $r_{ijt} - r_{mt}$) is affected by unanticipated innovation of the information variables of firm i as well as by those of the average firm in the market portfolio.

The second approach is to adopt the theory of CAPM (Capital Asset Pricing Model) in order to incorporate risk-averse investors.[4] Then, the arbitrage condition of equation (3.9) is replaced by the following CAPM formula:

$$E_{t-1}(r_{ijt}) - r_f = \beta_{ij}(E_{t-1}(r_{mt}) - r_f) \tag{3.11}$$

which gives the following definition of the excess rate of return to capital:

$$ER^C_{ijt} \equiv r_{ijt} - \beta_{ij}r_{mt} - (1 - \beta_{ij})r_f$$

[4]Here, as was in G&L, we follow the convention of the event-study literature where the 'abnormal' (*or* excess) returns to stock capital is measured by the deviation from the 'normal' return which is predicted by CAPM.

where ER^C_{ijt} denotes the excess return of firm i under the CAPM assumption, defined by the realized rate of return of firm i's equity over the one predicted by CAPM. As before, by plugging equations (3.7) and (3.8) above, we have

$$\begin{aligned} ER^C_{ijt} &\equiv r_{ijt} - \beta_{ij} r_{mt} - (1-\beta_{ij}) r_f \\ &= \theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) - \beta_{ij}\theta_m(z_{mt} - E_{t-1}(z_{mt})) \\ &\quad + \{E_{t-1}(r_{ijt}) - \beta_{ij} E_{t-1}(r_{mt}) - (1-\beta_{ij}) r_f\} \\ &= \theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) - \beta_{ij}\theta_m(z_{mt} - E_{t-1}(z_{mt})) \qquad (3.12) \end{aligned}$$

where equation (3.11) was used to derive the last equality above.

3.3 Empirical Specifications

Note that in equations (3.10) and (3.12), the excess rates of return to capital are expressed as a linear combination of the forecasting errors of the information variables, z_{ijt} and z_{mt}. Thus, we need to further specify the stochastic processes generating the components of these variables to provide an empirically implementable expression for the right-hand sides of equations (3.10) and (3.12). In addition, in the case of the CAPM specification, we also need to estimate β_{ij} from the data since this variable is unobservable.

First, with the CAPM specification, the excess rate of return to capital is measured by[5]

$$ER^C_{ijt} \equiv r_{ijt} - \beta_{ij} r_{mt} - (1-\beta_{ij}) r_f \qquad (3.13)$$

[5]Measuring $ER^N_{ijt} \equiv r_{ijt} - r_{mt}$ is straightforward. r_{ijt} and r_{mt} are the realized rate of return to firm i's equity and its market average, respectively, which are directly taken from CRSP database. See data appendix for detailed data description.

To estimate β_{ij}, we write the market model from the finance literature

$$r_{ijt} = a_{ij} + b_{ij} r_{mt} + \epsilon_{ijt} \tag{3.14}$$

Then one can show that under the hypothesis that CAPM is valid, the OLS estimates $\hat{a}_{ij}$ and $\hat{b}_{ij}$ converge in probability to $(1 - \beta_{ij})r_f$ and β_{ij} respectively.[6] Thus, the excess rate of return with CAPM specification can be calculated by

$$ER^C_{ijt} = \hat{\epsilon}_{ijt} = r_{ijt} - \hat{b}_{ij} r_{mt} - \hat{a}_{ij} \tag{3.15}$$

Next, following Grossman (1987) and G&L, we assume that reduced-form operating profits (z_{ijt}) depend on wage (w_t), energy price (p^e_t) and output price (p_{jt}).[7] The market clearing output price is assumed to be written as $p_{jt} = f\left(p^m_{jt}, y_t, p^d_t\right)$, where p^m_{jt} denotes the import price of industry j at time t (which is exogenously given by the small open economy assumption), y_t denotes aggregate income of the domestic economy and p^d_t denotes the price of competing domestic goods. Then, with log linear approximation and by adding white-noise error term (u_{ijt}), we can decompose z_{ijt} as follows:

$$z_{ijt} = \alpha_{ij1} p^m_{jt} + \alpha_{ij2} w_t + \alpha_{ij3} p^e_t + \alpha_{ij4} y_t + \alpha_{ij5} p^d_t + u_{ijt} \tag{3.16}$$

Analogously, for the average market portfolio we write

$$z_{mt} = \alpha_{m1} p^m_t + \alpha_{m2} w_t + \alpha_{ij3} p^e_t + \alpha_{m4} y_t + \alpha_{m5} p^d_t + u_{mt} \tag{3.17}$$

[6]This was first shown in Fama (1973). The advantage of this approach is that we don't need to obtain the data on rate of return to risk-free asset (r_f). See also Cambell, Lo and MacKinaly (1997) who who provides extensive survey on the event-study literature in finance where the measurement of the normal (and thus abnormal) stock return is frequently required to analyze the impact of each event.

[7]Hereafter, all lowercase letters denote the logarithms of each variable except r.

Note that in equation (3.17), we include the average import price (p_t^m) instead of industry-specific import price variable (p_{jt}^m). Then, the two components of $z_{ijt} - E_{t-1}(z_{ijt})$ and $z_{mt} - E_{t-1}(z_{mt})$ in the right-hand sides of equations (3.10) and (3.12) can be written as the forecasting error of each variable in the right-hand sides of (3.16) and (3.17) with information available at period $t-1$.

That is,

$$z_{ijt} - E_{t-1}(z_{ijt}) = \alpha_{ij1}\overline{p_{jt}^m} + \alpha_{ij2}\overline{w_t} + \alpha_{ij3}\overline{p_t^e} + \alpha_{ij4}\overline{y_t} + \alpha_{ij5}\overline{p_t^d} + \overline{u_{ijt}} \quad (3.18)$$

$$z_{mt} - E_{t-1}(z_{mt}) = \alpha_{m1}\overline{p_t^m} + \alpha_{m2}\overline{w_t} + \alpha_{ij3}\overline{p_t^e} + \alpha_{ij4}\overline{y_t} + \alpha_{ij5}\overline{p_t^d} + \overline{u_{mt}} \quad (3.19)$$

where $\overline{x_t}$ represents forecasting error (or "news") of variable x_t with information available at time $t-1$ (i.e., $\overline{x_t} \equiv x_t - E_{t-1}(x_t)$ for any x_t). In constructing the news variables in equation (3.18) and (3.19), we proceed as follows. First, for the industrial import price p_{jt}^m, we assume that this variable contain a trend component and that it depends on its own lagged values and the lagged values of industry-specific foreign exchange rates and industry-specific foreign wages.[8]

Formally, we assume that p_{jt}^m follows the following multivariate autoregressive process[9]

$$p_{jt}^m = p_{j0}^m + \sum_{\tau=1}^{4} \rho_{pj\tau} p_{j,t-\tau}^m + \sum_{\tau=1}^{8} \rho_{wj\tau} w_{j,t-\tau}^m + \sum_{\tau=1}^{8} \rho_{ej\tau} e_{j,t-\tau}^m + v_{jt} \quad (3.20)$$

where w_{jt}^m and e_{jt}^m are foreign countries' wage rates and exchange rates weighted by

[8]In principle, the import price may depend on other variables such as various factor prices and technology improvement in the trade partner countries. However, these variables are not only unobservable but also the stock market investors are unlikely to keep track on all these variables in forming an expectation about p_{jt}^m.

[9]In all estimation equations to construct the news variables below, all variables are logs of quadratically detrended and deseasonalized series. For notational simplicity, we use the same notation for the variables as before.

import share for each industry and v_{jt} is a white-noise error term. Then, the news variable for the industrial import price is obtained from the residuals of equation (3.20), i.e.,

$$\overline{p_{jt}^m} = \hat{v}_{jt} = p_{jt}^m - \hat{p}_{j0}^m - \sum_{\tau=1}^{4} \hat{\rho}_{pj\tau} p_{j,t-\tau}^m - \sum_{\tau=1}^{8} \hat{\rho}_{wj\tau} w_{j,t-\tau}^m - \sum_{\tau=1}^{8} \hat{\rho}_{ej\tau} e_{j,t-\tau}^m \tag{3.21}$$

Further, we assume that the industry-specific foreign wage and foreign exchange rate variables follow fourth-order univariate autoregressive processes with residuals $\overline{w_{jt}^m}$ and $\overline{e_{jt}^m}$. Then we can see that $p_{jt}^m - E_{t-1}(p_{jt}^m) = \overline{p_{jt}^m}$ and that $E_t(p_{j,t+\tau}^m) - E_{t-1}(p_{j,t+\tau}^m)$ is a linear combination of $\overline{p_{jt}^m}$, $\overline{w_{jt}^m}$ and $\overline{e_{jt}^m}$ for all $\tau > 0$. In other words, although the unexpected shock to foreign exchange rate and foreign wage variables do not affect the current profits to deviate from their expected level, they have an impact on the actual stock market deviation from its expected value by updating the beliefs about future import prices. Therefore, $\overline{w_{jt}^m}$ and $\overline{e_{jt}^m}$ will also be included as components of $z_{ijt} - E_{t-1}(z_{ijt})$ in the final empirical specifications.

Forecast errors about the other macro variables which are common in equations (3.18) and (3.19) ($\overline{w_t}$, $\overline{p_t^e}$, $\overline{y_t}$ and $\overline{p_t^d}$) are obtained by assuming that these variables follow a vector autoregressive process including the money stock.[10] Again, the residuals of the VAR estimation are taken for each news variable. Finally, we obtain the aggregate import price news $\overline{p_t^m}$ by taking the residuals of the fourth-order univariate autoregressive model.

Using the stochastic process for each variable explained above, we can write

$$\theta_{ij}(z_{ijt} - E_{t-1}(z_{ijt})) \;=\; \delta_{i1}\overline{p_{jt}^m} + \delta_{i2}\overline{e_{jt}^m} + \delta_{i3}\overline{w_{jt}^m} + \delta_{i5}\overline{w_t}$$

[10] Although the money stock does not affect the profitability directly, it plays a significant role as a leading indictor of other variables which is confirmed by our VAR estimation results.

$$+\delta_{i6}\overline{p_t^e} + \delta_{i7}\overline{y_t} + \delta_{i8}\overline{p_t^d} + \delta_{i9}\overline{s_t} + \mu_{ijt} \quad (3.22)$$

$$\begin{aligned} \theta_m(z_{mt} - E_{t-1}(z_{mt})) &= \delta_{m4}\overline{p_t^m} + \delta_{m5}\overline{w_t} + \delta_{m6}\overline{p_t^e} + \delta_{m7}\overline{y_t} \\ &\quad + \delta_{m8}\overline{p_t^d} + \delta_{m9}\overline{s_t} + \mu_{mt} \end{aligned} \quad (3.23)$$

where $\delta_{ijk} \equiv \theta_{ij}\alpha_{ijk}$ and $\delta_{mk} \equiv \theta_m\alpha_{mk}$ for all k. $\overline{s_t}$ denotes the unexpected change of aggregate money supply in the economy calculated by VAR estimation above. Plugging equations (3.22) and (2.23) into equations (3.10) and (3.12), we finally derive two empirical specifications such that

$$\begin{aligned} ER_{ijt}^N &= \gamma_{ij1}\overline{p_{jt}^m} + \gamma_{ij2}\overline{e_{jt}^m} + \gamma_{ij3}\overline{w_{jt}^m} + \gamma_{ij4}\overline{p_t^m} + \gamma_{ij5}\overline{w_t} \\ &\quad + \gamma_{ij6}\overline{p_t^e} + \gamma_{ij7}\overline{y_t} + \gamma_{ij8}\overline{p_t^d} + \gamma_{ij9}\overline{s_t} + \nu_{ijt} \end{aligned} \quad (3.24)$$

$$\begin{aligned} ER_{ijt}^C &= \lambda_{ij1}\overline{p_{jt}^m} + \lambda_{ij2}\overline{e_{nt}^m} + \lambda_{ij3}\overline{w_{nt}^m} + \lambda_{ij4}\overline{p_t^m} + \lambda_{ij5}\overline{w_t} \\ &\quad + \lambda_{ij6}\overline{p_t^e} + \lambda_{ij7}\overline{y_t} + \lambda_{ij8}\overline{p_t^d} + \lambda_{ij9}\overline{s_t} + \eta_{ijt} \end{aligned} \quad (3.25)$$

where $\gamma_{ijk} \equiv \delta_{ijk}$ and $\lambda_{ijk} \equiv \delta_{ijk}$ for $k = 1, 2, 3$, $\gamma_{ijk} \equiv -\delta_{m4}$ and $\lambda_{ijk} = -\beta_{ij}\delta_{m4}$ for $k = 4$ and $\gamma_{ijk} \equiv \delta_{ijk} - \delta_{mk}$ and $\lambda_{ijk} \equiv \delta_{ijk} - \beta_{ij}\delta_{mk}$ for $k = 5, \cdots, 9$. Note that from the empirical stand point, the only difference between two types of specifications (risk-nutral and CAPM) is the definitions of excess rate of return in the left-hand sides of equations (2.24) and (2.25).

Recall that our goal in this paper is to estimate the effects of import price on the excess return to capital in the 'import-competeing' industries. This effect is captured by the coefficients γ_{ij1} and λ_{ij1} of equations (2.24) and (2.25) and the theory predicts that these coefficients should be non-negative for import-competing industries: the unexpected decrease of import price (i.e., the increase of import competition) in industry j will lower the excess return on firm i's equity in the same sector.

However, the theory and the empirical methodology described above do not tell us about how to define 'import-competing' industries. In other words, equations (2.24) and (2.25) can be estimated industry by industry (which is exactly what G&L did) under *a priori* assumption by a researcher that the industry chosen for the regression is characterized by import-competing industry. But what should be the criterion to choose such an industry? For this reason, we modify equations (2.24) and (2.25) by introducing the interaction between industrial import penetration ratio and its import price change, where the import penetration ratio serves as a tentative proxy for the degree of import competition.[11] Then, the modified version of the estimation equations are written as

$$\begin{aligned} ER^N_{ijt} &= \gamma_{ij1} q_{jt} \overline{p^m_{jt}} + \gamma_{ij2} \overline{e^m_{jt}} + \gamma_{ij3} \overline{w^m_{jt}} + \gamma_{ij4} \overline{p^m_t} + \gamma_{ij5} \overline{w_t} \\ &\quad + \gamma_{ij6} \overline{p^e_t} + \gamma_{ij7} \overline{y_t} + \gamma_{ij8} \overline{p^d_t} + \gamma_{ij9} \overline{s_t} + \nu_{ijt} \qquad (3.26) \\ ER^C_{ijt} &= \lambda_{ij1} q_{jt} \overline{p^m_{jt}} + \lambda_{ij2} \overline{e^m_{nt}} + \lambda_{ij3} \overline{w^m_{nt}} + \lambda_{ij4} \overline{p^m_t} + \lambda_{ij5} \overline{w_t} \\ &\quad + \lambda_{ij6} \overline{p^e_t} + \lambda_{ij7} \overline{y_t} + \lambda_{ij8} \overline{p^d_t} + \lambda_{ij9} \overline{s_t} + \eta_{ijt} \qquad (3.27) \end{aligned}$$

where q_{jt} stands for the import penetration ratio of industry j at time t which is defined by 'import volume / value added' for each industry.[12]

In equation (2.26) and (2.27), the elasticity of excess rate of return to capital to the unexpected change in import price equals $\gamma_{ij1} q_{jt}$ and $\lambda_{ij1} q_{jt}$. It follows that if

[11] In Revenga (1992) which studied the impact of import competition on the labor market behavior in the US, she incorporated the interaction term between import penetration ratio and import price in a similar way.

[12] There are several ways to define the import penetration ratio in the previous literature. The alternative definitions are $\frac{\text{import}}{\text{import + export}}$, $\frac{\text{import}}{\text{import + domestic shipment}}$ and $\frac{\text{import}}{\text{domestic absorption}}$. We also calculated these ratios but these alternatives did not change the main finding of this paper.

γ_{ij1} (or λ_{ij1}) are the same for given industries, the elasticity varies across industries in proportion to the import penetration ratio.[13] Then, we have two different sets of estimation strategies. First, we can estimate equations (2.24) and (2.25) for each 'import-competing' industries with industrial panel data by stacking all firms in the given industry. That is, for each industry j, we estimate

$$Y_j = X_j\zeta_j + \nu_j \tag{3.28}$$

where Y_j is $(NT \times 1)$ industrial column vector of excess rate of return, X_j is $(NT \times 10)$ matrix of regressors including constant and ζ_j is (10×1) parameter vectors to be estimated. In doing so, we treat equation (2.28) as a random-effect model with time component.[14] Second, by introducing the interaction term between import penetration and import price (and thus by controlling for the import-competitiveness of the industries), equations (2.26) and (2.27) can be estimated for the manufacturing sector as a whole after stacking equation (2.28) by industrial block. That is, we write

$$Y = X\zeta + \nu \tag{3.29}$$

where Y is $(NJT \times 1)$ industrial column vector of excess rate of return, X is $(NTJ \times 10)$ matrix of regressors including constant, ζ is (10×1) parameter vectors to be estimated and J is the number of industries in the sample. Again, we estimate this with a random-effects model with time components. We now turn to the estimation

[13] This interaction with the import penetration ratio could be introduced in other foreign country variables such as $\overline{e^m_{jt}}$ and $\overline{w^m_{jt}}$ as well. We consider this specification also when we present the estimation results in Section 2.4.

[14] Since any predictable firm specific shock is ruled out by the arbitrage transactions in the efficient market hypothesis, the firm specific component is not included.

results.

3.4 Estimation Results

3.4.1 Industrial Regressions

First, we estimate equation (2.24) and (2.25) (or equation (2.28) in the stacked form) for each industry. Again, recall that the main goal of this section is to see if the unanticipated changes in import prices have significant effect on the excess rate of return to capital in the import-competing industry. The magnitude and the sign of this effect is captured by γ_{j1} with risk neutrality assumption and by λ_{j1} with CAPM specification. In the import-competing industry, these coefficients are expected to be non-negative. If stock market capital is perfectly mobile, the investors in the (forward-looking) efficient stock market will respond to the unanticipated shock to the import price by moving their capital into other industries, thereby equalizing the rate of return to capital in the stock market. In this case, these coefficients are expected to be zero. On the other hand, if the mobility of stock market capital is imperfect, the unanticipated fall in the import price (which threatens the current and the future profiles of the firm's profits) will have negative impact on the performance of the firm's equity. If this is the case, we expect the coefficients should be positive.

Then, the first task to estimate equation (2.28) is to identify which industries are import-competitive. Since the theory provides little guidance, we choose the same industries as in G&L.[15] The results are shown in Table 3.1 and Table 3.2 where the

[15]The sample industries consist of five three-digit SIC industries (SIC 2420, 2620, 3010, 3310 and 3450) and one two-digit SIC industry (SIC 3200). In G&L, the only criterion to choose these industries in the sample was 'the availability of reasonably long time-series data' of industrial import price index.

sample time period is also restricted to be the same as in G&L (which ends at the fourth quarter of 1986). We confirm that the similar pattern emerges as in G&L. With risk neutrality specification (Table 3.1), the estimated coefficient on industrial import prices (p^m_{jt}) are positive in five cases out of six industries and are significant in four cases. Under the CAPM specification (Table 3.2), all positive estimated coefficients (five cases out of six) are statistically significant. Thus, as was in G&L, we may conclude that the industrial import price change had expected effects on the excess rate of return to capital and that the hypothesis of perfect capital mobility has been rejected.

However, one may question what the results would be with the same industrial choice but with longer time-series data. Since we obtained extended sample period spanning up to the fourth quarter of 1992, we estimate the model with our data, which are presented in Table 3.3 and 3.4. Surprisingly, the results appear to run into almost the opposite direction with the extended data. In Table 3.3 (which is the estimation results with risk neutrality assumption), only two industries (SIC 3200 and 3450) remain to have significantly positive coefficients on the industrial import prices variable (both at 10% confidence level). Even in these industries with positive coefficients, the estimates became much smaller with the extended data (the coefficient became 0.720 from 0.792 for SIC 3200 and 0.779 from 1.204 for SIC 3450). When estimated under the CAPM specification, the results are more strikingly reversed: only one industry (SIC 3450) remains to have significantly positive coefficient estimate on industrial import price variable. And the magnitude of the estimated coefficient also decreased substantially from 1.198 to 0.747.

These results with our longer time-series data set seem to almost completely contradict G&L's results: the effects of import competition on the rate of return to capital are indistinguishable from zero in five out of six manufacturing industries and thus the data supports the perfect capital mobility (in favor of Heckscher-Ohlin model) over the Specific-Factors model. But can we conclude that these results are representing the overall relationship between import price and stock market behavior in the US? As was mentioned in the last section, when G&L chose these six industries in their sample, the data availability was the only criterion and therefore these results may be subject to data selection bias. Since, our data allow us to expand the industry coverage up to 22 manufacturing industries, we now turn to the analysis with our full data sets (for 22 manufacturing industries over the period of 1974 – 1992).

3.4.2 Incorporating Import Competitiveness

In analyzing our extended data set, we modified the estimation procedure as was described in Section 2.3. That is, we introduce the interaction term between import penetration ratio of each industry and its import price index (where import penetration ratio could provide the information on the degree of import competition in each industry).[16] Then, our modified estimation equations are specified in equations (2.26) and (2.27) (or (2.29) in stacked form). Before proceeding, we categorized the 22 industries into the ones with high, medium and low import penetration ratios according to the level of its import penetration ratios for the future use in Table

[16]Introducing this interaction term is based on the assumption that the higher the import penetration rate in an industry, the higher the degree of the import competition in the given industry.

3.5.[17]

We first present the estimation results with all 3-digit industries in the sample, which is shown in Table 3.6. The first three columns ((i)-(iii)) and the second three columns ((iv)-(vi)) are the results with risk neutrality specification and with CAPM specification, respectively. When the interaction between import penetration ratios and other foreign variables are not considered (column (i) and (iv)), we find that the import price elasticities of excess rate of returns are positive (0.075 and 0.076 respectively) but not distinguishable from zero at any standard significance level.

However, when these interaction terms are incorporated for import prices ((ii) and (v)), the import price elasticities become significantly different from zero at 5% level. In these cases, we cannot reject the hypotheses that these coefficients are greater than zero with one-tailed test, which implies that the perfect capital mobility hypotheses are rejected by our data. When the interaction terms with import penetration ratios were added to other foreign variables (industry specific foreign exchange rates and foreign wage rates), the import price elasticities are significant only for the case of CAPM specification.

Next, we run the same regressions only for the high import penetration industries categorized in Table 3.5. The results are presented in Table 3.7. As expected, the results are more pronounced than those with all industries included. The estimated coefficients for import prices are still insignificant when we didn't include any interaction terms with import penetration ratios in the regression (column (i) and (iv)).

[17]See the table for descriptions of each industries and how the import penetration ratios are defined and categorized

However, when the interaction terms are included either only for import prices ((ii) and (v)) or for all foreign variables including foreign exchange rates and foreign wage rates (iii) and (vi))), the import price elasticities are significantly different from zero at 5% or 10% level.

In this section, we presented the estimation results of the model with (and without) the interaction term between industrial import price (or all three foreign variables) and import penetration ratios. Overall then, including those interaction terms has revealed that unlike the industry-by-industry analysis, the unanticipated import price changes have significant positive impact on the excess rate of return to capital and that the hypothesis of perfect capital mobility across industries are rejected by the data.

3.4.3 Further Discussion on the Estimation Results

Up until now, we discussed the estimation results focusing only on the signs and the significance of the estimated import price elasticities. In this section, we discuss the possible interpretations on the 'size' of the import price elasticities and how plausible the estimated coefficients on other variables are.

Although we have used the term 'elasticities' to denote the estimated coefficients on the import price variable, the 'actual' import price elasticities for equation (2.26) and (2.27) are the estimated coefficients multiplied by the import penetration ratios. Table 3.8 shows these actual elasticity of excess rate of return with respect to unanticipated import price shock for high import penetration ratio industries. In G&L, they calculated the Stolper-Samuelson derivatives that would prevail in a simple static model with no capital mobility which is near or slightly above one with most plausible values of parameters. In Table 3.8, we see that all of these elasticities are far less than one (the highest number is the import price elasticity of Radio and TV equipment (SIC 3650) in 1990). This implies that although the hypothesis of the perfect capital mobility across industries were statistically rejected in the previous subsection, it is equally unlikely that the stock market capital is completely industry-specific.

Next, we consider the signs of the coefficients on the variables other than industrial import prices for the high import penetration ratio industries (Table 3.7). First, we found both the industry-specific foreign exchange rates and the industry-specific foreign wage rates have positive effects on the excess rate of return.[18] These results

[18]The foreign exchange rates are calculated in terms of US dollar per foreign currency. Thus

are plausible since the depreciation of US dollar and the increase of foreign competitors' input costs will give advantage for domestic producers over their foreign competitors.

The interpretations of other variables are less clear since we estimated only the reduced-form equations. The aggregate import prices and the domestic producer price index are the proxied for the prices of other competing import and domestic goods' prices. Assuming the cross elasticity of demand with respect to other competing goods' prices are negative, the positive shocks to these variables will increase the demand for the output of the given industry. Therefore, the coefficients on these variables are expected to be positive and indeed we found that this is the case although the estimated coefficients on domestic producer price index are not statistically significant. The aggregate money supply shock which serves as a macro economic leading indicator and the energy price shock have the positive and the negative signs as was expected.

3.5 Concluding Remarks

Building on the framework developed by Pakes (1981, 1985) and Grossman and Levinsohn (1989), this paper investigates the effects of import competition on the stock market rate of return to capital. Using comprehensive firm level panel data on twenty two US manufacturing industries from the period 1974-1992, We find that unanticipated changes in import prices have statistically significant effects on the excess rate of return to capital in the import-competing industries. The hypothesis

increase in foreign exchange rate implies the depreciation of US dollar.

of perfect capital mobility across industries, as postulated in the Heckscher-Ohlin model of international trade, is thus rejected by the data.

At the same time, however, the size of the estimated coefficients indicate that the stock market capital is not entirely industry-specific, in contrast to assumptions made in the Specific-Factors model of trade. These results suggest that estimation of the impact of trade policy changes or other changes in the external environment on factor prices need to be based on models which allow for intermediate degrees of factor mobility.

Table 3.1: Industrial regression with the same sample choice as in Grossman and Levinsohn (1989) (Random effects model with time components)

	SIC Code					
	2420	2620	3010	3200	3310	3450
Dependent variable : excess return with risk neutrality						
News variables						
p_{jt}^m	0.333 (0.296)	0.702** (0.347)	-0.236 (0.910)	0.792** (0.396)	0.966* (0.556)	1.204** (0.475)
e_{jt}^m	-0.515 (0.687)	-0.285 (0.290)	0.411 (0.351)	0.122 (0.237)	-0.022 (0.192)	0.395 (0.282)
w_{jt}^m	-3.918** (1.907)	-1.109** (0.521)	0.439 (2.667)	3.341** (1.429)	8.068*** (1.672)	-1.955 (1.464)
p_t^m	0.974 (1.041)	0.767* (0.417)	-0.772 (0.893)	-0.279 (0.444)	-0.282 (0.535)	-0.405 (0.687)
s_t	4.710*** (1.525)	1.995*** (0.730)	0.207 (1.286)	2.000*** (0.733)	0.902 (0.816)	4.596*** (1.116)
y_t	0.596 (1.592)	0.255 (0.696)	2.731* (1.424)	0.429 (0.845)	4.442*** (0.978)	2.175* (1.141)
w_t	2.356 (2.286)	-0.682 (0.991)	8.134*** (2.046)	0.820 (1.157)	0.847 (1.272)	0.087 (1.616)
p_t^e	-0.484 (0.467)	-0.547*** (0.206)	-0.679** (0.407)	-0.587** (0.238)	-1.056*** (0.316)	-0.408 (0.346)
p_t^d	1.307 (1.879)	0.147 (0.835)	4.225** (1.686)	1.362 (0.968)	2.264* (1.248)	1.405 (1.296)
Contant	0.021 (0.018)	0.017** (0.007)	0.020* (0.011)	0.010 (0.008)	-0.022*** (0.008)	-0.009 (0.009)
R^2	0.251	0.179	0.154	0.343	0.340	0.383
Number of firms	3	11	5	21	16	7
Sample period	'74 Q2 - '86 Q4	'74 Q1 - '86 Q4	'76 Q2 - '86 Q4	'78 Q3 - '86 Q4	'78 Q3 - '86 Q4	'74 Q2 - '86 Q4

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.2: Industrial regression with the same sample choice as in Grossman and Levinsohn (1989) (Random effects model with time components)

	SIC Code					
	2420	2620	3010	3200	3310	3450
Dependent variable : excess return with CAPM prediction						
News Variables						
p^m_{jt}	0.559** (0.237)	0.673* (0.348)	-0.223 (0.896)	0.859** (0.395)	1.290** (0.556)	1.198** (0.478)
e^m_{jt}	0.110 (0.670)	-0.332 (0.290)	0.685** (0.346)	0.403* (0.236)	0.096 (0.191)	0.345 (0.284)
w^m_{jt}	-4.231** (1.861)	-1.040** (0.521)	0.119 (2.627)	2.682* (1.426)	8.198*** (1.670)	-1.921 (1.471)
p^m_t	1.181 (1.016)	0.746* (0.418)	-0.811 (0.879)	-0.221 (0.443)	-0.296 (0.534)	-0.382 (0.691)
s_t	3.930*** (1.488)	2.052*** (0.731)	-0.277 (1.266)	1.913*** (0.732)	0.922 (0.815)	4.673*** (1.121)
y_t	0.381 (1.553)	0.297 (0.697)	2.939** (1.402)	0.418 (0.843)	4.362*** (0.977)	2.203* (1.147)
w_t	2.214 (2.231)	-0.687 (0.992)	8.265*** (2.015)	0.635 (1.155)	0.467 (1.270)	0.148 (1.624)
p^s_t	-0.372 (0.455)	-0.552*** (0.206)	-0.652 (0.401)	-0.558** (0.238)	-1.135*** (0.316)	-0.417 (0.347)
p^d_t	1.020 (1.834)	0.187 (0.836)	4.006** (1.660)	1.152 (0.967)	2.548** (1.247)	1.378 (1.302)
Contant	0.000 (0.018)	0.003 (0.007)	-0.002 (0.011)	-0.001 (0.008)	-0.011 (0.008)	-0.010 (0.009)
R^2	0.229	0.181	0.153	0.284	0.349	0.378
Number of firms	3	11	5	21	16	7
Sample period	'74 Q2 - '86 Q4	'74 Q1 - '86 Q4	'76 Q2 - '86 Q4	'78 Q3 - '86 Q4	'78 Q3 - '86 Q4	'74 Q2 - '86 Q4

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.3: Industrial regression with extended sample period (Random effects model with time components)

	SIC Code					
	2420	2620	3010	3200	3310	3450
Dependent variable : excess return with risk neutrality						
News Variables						
p^m_{jt}	0.055 (0.257)	0.001 (0.228)	-0.052 (0.750)	0.720* (0.391)	0.210 (0.483)	0.779* (0.409)
e^m_{jt}	-0.464 (0.551)	-0.539** (0.219)	0.375 (0.248)	0.384** (0.193)	0.125 (0.162)	0.408** (0.205)
w^m_{jt}	-1.716 (1.622)	0.369 (0.646)	-2.312 (2.130)	2.665* (1.548)	2.700* (1.598)	-1.453 (1.364)
p^m_t	0.454 (0.771)	0.440 (0.319)	-0.380 (0.647)	-1.118** (0.442)	-0.161 (0.505)	-1.548*** (0.556)
s_t	2.921** (1.161)	1.377*** (0.482)	-0.723 (0.926)	1.657** (0.678)	0.084 (0.743)	2.805*** (0.538)
y_t	0.329 (1.423)	0.597 (0.568)	1.663 (1.138)	0.045 (0.897)	3.044*** (1.026)	1.849* (1.020)
w_t	1.760 (1.889)	-0.860 (0.767)	6.881*** (1.433)	1.406 (1.075)	-0.108 (1.189)	-0.285 (1.300)
p^e_t	-0.002 (0.363)	-0.267* (0.149)	-0.385 (0.292)	0.114 (0.225)	-0.213 (0.248)	-0.101 (0.270)
p^d_t	-0.253 (1.697)	0.634 (0.690)	2.865** (1.391)	0.110 (1.083)	0.247 (1.179)	2.271** (1.215)
Contant	0.013 (0.010)	0.008 (0.005)	0.021** (0.011)	0.006 (0.007)	-0.016** (0.007)	-0.007 (0.008)
R^2	0.111	0.103	0.267	0.187	0.085	0.297
Number of firms	3	11	5	21	16	7
Sample period	'74 Q2 - '92 Q4	'74 Q1 - '92 Q4	'76 Q2 - '92 Q4	'78 Q3 - '92 Q4	'78 Q3 - '92 Q4	'74 Q2 - '92 Q4

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.4: Industrial regression with extended sample period (Random effects model with time components)

	SIC Code					
	2420	2620	3010	3200	3310	3450
Dependent variable : excess return with CAPM prediction						
News Variables						
p_{jt}^m	-0.022 (0.248)	-0.009 (0.228)	-0.391 (0.743)	0.562 (0.390)	0.495 (0.481)	0.747* (0.410)
e_{jt}^m	0.004 (0.531)	-0.568** (0.219)	0.425* (0.245)	0.336* (0.192)	0.114 (0.161)	0.400** (0.206)
w_{jt}^m	-1.777 (1.564)	0.372 (0.647)	-2.012 (2.108)	2.691* (1.544)	3.363** (1.591)	-1.486 (1.370)
p_t^m	0.378 (0.744)	0.444 (0.319)	-0.535 (0.640)	-1.182*** (0.441)	-0.292 (0.503)	-1.514*** (0.558)
s_t	2.825** (1.120)	1.381*** (0.482)	-0.734 (0.916)	1.712** (0.676)	0.227 (0.739)	2.807*** (0.842)
y_t	0.163 (1.373)	0.611 (0.568)	1.527 (1.126)	0.121 (0.894)	2.913*** (1.021)	1.909* (1.025)
w_t	0.412 (1.822)	-0.786 (0.767)	5.722*** (1.419)	-0.048 (1.072)	-1.233 (1.184)	0.007 (1.306)
p_t^e	0.041 (0.350)	-0.268* (0.149)	-0.373 (0.289)	0.104 (0.224)	-0.237 (0.247)	-0.100 (0.271)
p_t^d	0.345 (1.637)	0.598 (0.690)	3.513** (1.377)	0.384 (1.081)	0.746 (1.173)	2.114* (1.221)
Contant	-0.007 (0.010)	-0.006 (0.005)	-0.001 (0.011)	-0.004 (0.007)	-0.004 (0.007)	-0.008 (0.008)
R^2	0.097	0.106	0.249	0.165	0.106	0.283
Number of firms	3	11	5	21	16	7
Sample period	'74 Q2 - '92 Q4	'74 Q1 - '92 Q4	'76 Q2 - '92 Q4	'78 Q3 - '92 Q4	'78 Q3 - '92 Q4	'74 Q2 - '92 Q4

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.5: Import Penetration Ratios of Sample Industries

SIC Code	Descriptions	Import Penetration Ratios[1] def1	def2	def3	def4	Categorization according to def1[2]
3-digit Industries						
2010	Meat and Meat Packing Prod.	0.22	0.21	0.58	0.04	high
2310	Men's or Boys' Suits	0.26	0.19	0.87	0.12	high
2420	Lumber, Cooperage etc.	0.43	0.34	0.74	0.15	high
2620	Paper Mill	0.42	0.32	0.83	0.16	high
3010	Tires and Inner Tubes	0.21	0.18	0.61	0.09	high
3310	Rolling and Finishing Mill	0.33	0.25	0.75	0.11	high
3330	Smelter and Refined Nonferr Met.	1.28	0.74	0.73	0.24	high
3450	Nuts, Screws, Rivets etc.	0.22	0.19	0.67	0.11	high
3650	Radios and TV Equipment	1.61	0.58	0.79	0.32	high
3710	Motor Vehicles and Parts	0.57	0.39	0.61	0.15	high
3830	Optical Instruments and Lenses	0.26	0.27	0.49	0.14	high
2080	~~Beverages and Flavoring~~ Extracts	0.14	0.12	0.86	0.06	medium
3350	Rolled, extruded nonferr metals	0.15	0.16	0.48	0.04	medium
3530	Const., Mining, Oil-Field Equip.	0.14	0.22	0.17	0.06	medium
3540	Metal Working Mach. Equip.	0.16	0.15	0.40	0.09	medium
3560	General Industrial Machinery	0.14	0.14	0.31	0.07	medium
3640	Electric Lighting & Wiring Eq.	0.10	0.10	0.36	0.05	medium
3690	Electrical Mach. Equip.	0.20	0.20	0.37	0.09	medium
3820	Measuring and Controlling Inst.	0.11	0.14	0.22	0.06	medium
3860	Photographic Equip. and Supplies	0.17	0.16	0.44	0.10	medium
2020	Dairy Products	0.06	0.06	0.51	0.01	low
3070	Miscellaneous Plastic Products	0.07	0.07	0.39	0.03	low

Note: 1. The import penatration ratios are defined as follows: defl = import / value-added, def2 = import / absorption, def3 = import / import + export and def4 = import / import + domestic shipment.
2. The industrial categorizations are defined as follows: high import penetration industries if defl ≥ 0.20, medium import penetration industries if $0.10 \leq$ defl < 0.20 and low import penetration industreis if defl < 0.10.

Table 3.6: Panel Data Estimation of All Industries (3-digit Level SIC Code Industries)

News Variables	Dependent Variable: Excess Rate of Return with Risk Neutrality (ER^N)			with CAPM (ER^C)		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\overline{p^m_{jt}}$	0.075			0.076		
	(0.117)			(0.116)		
$q_{jt}\overline{p^m_{jt}}$		0.165**	0.151		0.180**	0.120**
		(0.082)	(0.118)		(0.082)	(0.053)
$\overline{e^m_{jt}}$	0.277***	0.304***		0.254***	0.285***	
	(0.044)	(0.047)		(0.044)	(0.046)	
$q_{jt}\overline{e^m_{jt}}$			0.336***			0.284***
			(0.054)			(0.054)
$\overline{w^m_{jt}}$	0.285	0.287		0.486*	0.488*	
	(0.260)	(0.260)		(0.258)	(0.258)	
$q_{jt}\overline{w^m_{jt}}$			0.580			0.722*
			(0.429)			(0.427)
$\overline{p_t}$	-0.465***	-0.487***	-0.509***	-0.563***	-0.588***	-0.560***
	(0.128)	(0.129)	(0.127)	(0.127)	(0.128)	(0.126)
$\overline{s_t}$	0.895***	0.910***	0.913***	0.968***	0.985***	0.986***
	(0.193)	(0.193)	(0.193)	(0.192)	(0.192)	(0.192)
$\overline{y_t}$	0.310	0.341	0.196	0.346	0.380	0.226
	(0.261)	(0.261)	(0.260)	(0.259)	(0.260)	(0.258)
$\overline{w_t}$	0.565*	0.612*	0.348	-0.157	-0.105	-0.359
	(0.291)	(0.292)	(0.287)	(0.289)	(0.290)	(0.286)
$\overline{p^e_t}$	-0.186***	-0.181***	-0.187***	-0.190***	-0.185***	-0.192***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
$\overline{p^d_t}$	0.666**	0.667**	0.726**	1.032***	1.034***	1.079***
	(0.305)	(0.305)	(0.305)	(0.304)	(0.304)	(0.303)
R^2	0.161	0.173	0.166	0.154	0.172	0.164
no. of firms	236					
no. of industries	22					
sample period	1974 Q1 - 1992 Q4					

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.7: Panel Data Estimation of High Import Penetration Industries (3-digit Level SIC Code Industries)

News Variables	Dependent Variable: Excess Rate of Return with Risk Neutrality (ER^N)			with CAPM (ER^C)		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\overline{p^m_{jt}}$	0.070			0.059		
	(0.113)			(0.112)		
$q_{jt}\overline{p^m_{jt}}$		0.249**	0.237**		0.241**	0.198*
		(0.124)	(0.113)		(0.123)	(0.112)
$\overline{e^m_{jt}}$	0.330***	0.342***		0.295***	0.306***	
	(0.072)	(0.072)		(0.071)	(0.071)	
$q_{jt}\overline{e^m_{jt}}$			0.263***			0.222***
			(0.052)			(0.051)
$\overline{w^m_{jt}}$	0.150	0.154		0.302	0.307	
	(0.356)	(0.356)		(0.354)	(0.354)	
$q_{jt}\overline{w^m_{jt}}$			0.573			0.635
			(0.425)			(0.422)
$\overline{p_t}$	0.444**	0.441**	0.485***	0.531***	0.528***	0.564***
	(0.183)	(0.183)	(0.182)	(0.182)	(0.182)	(0.181)
$\overline{s_t}$	0.566**	0.582**	0.604**	0.688**	0.705**	0.731***
	(0.278)	(0.278)	(0.278)	(0.276)	(0.276)	(0.276)
$\overline{y_t}$	0.760**	0.713*	0.651*	0.787**	0.740**	0.688**
	(0.379)	(0.379)	(0.378)	(0.376)	(0.377)	(0.376)
$\overline{w_t}$	0.507	0.473	0.250	-0.178	-0.211	-0.406
	(0.422)	(0.423)	(0.416)	(0.419)	(0.420)	(0.414)
$\overline{p^e_t}$	-0.142	-0.151*	-0.139	-0.150*	-0.159*	-0.146*
	(0.089)	(0.089)	(0.089)	(0.088)	(0.088)	(0.088)
$\overline{p^d_t}$	0.156	0.182	0.207	0.545	0.571	0.584
	(0.434)	(0.434)	(0.433)	(0.431)	(0.431)	(0.430)
R^2	0.111	0.149	0.141	0.103	0.121	0.151
no. of firms	97					
no. of industries	11					
sample period	1974 Q1 - 1992 Q4					

Notes: 1. Standard errors are in parentheses.
2. *, ** and *** represent that the coefficients are siginificantly different from zero at the 10%, 5% and 1% level, respectively. (two-tailed test)

Table 3.8: Actual Elasticity of Excess Rate of Return with respect to Unanticipated Import Price Shock (High Import Penetration Ratio Industries)

SIC Code	Descriptions	with Risk Neutrality				with CAPM			
		1975	1980	1985	1990	1975	1980	1985	1990
3-digit Industries									
2010	Meat (Packing) Prod.	0.050	0.069	0.051	0.047	0.048	0.067	0.050	0.045
2310	Men's or Boys' Suits	0.044	0.071	0.133	0.110	0.043	0.069	0.129	0.107
2420	Lumber, Cooperage etc.	0.084	0.118	0.166	0.110	0.081	0.115	0.160	0.106
2620	Paper Mill	0.098	0.103	0.115	0.117	0.095	0..100	0.112	0.113
3010	Tires & Inner Tubes	0.039	0.079	0.095	0.109	0.038	0.076	0.092	0.105
3310	Rolling & Finishing Mill	0.084	0.093	0.174	0.113	0.081	0.090	0.168	0.109
3330	Smelter & Refined Met.	0.193	0.410	0.869	0.330	0.187	0.396	0.841	0.320
3450	Nuts, Screws, etc.	0.053	0.059	0.085	0.100	0.051	0.057	0.083	0.097
3650	Radios & TV Equip.	0.236	0.278	0.828	0.924	0.228	0.269	0.801	0.895
3710	Motor Vehicles & Parts	0.137	0.213	0.261	0.275	0.132	0.206	0.252	0.266
3830	Optical Instruments	0.074	0.065	0.080	0.054	0.072	0.063	0.078	0.052

Notes: The calculations of the elasticities are based on the estimation results of equations (ii) and (v) in Table 3.7 and the industrial import penetration ratios in each year.

Appendix A

Appendix to Chapter One

A.1 Data Description

The selection of countries was mainly based on the availability of related data sets. These included five European countries (Denmark, France, Germany, Netherlands and United Kingdom) and three non-European countries (United States, Canada and Korea). All data pertained to 1980 and were converted into 1980 US dollars unless otherwise stated.

A.1.1 Industry Coverage and Labor Disaggregation

Industrial activities are disaggregated according to ISIC classification system (Rev.2, 1968) with one digit level for non-manufacturing (eight sectors) and two digit level for manufacturing (nine sectors), which gives total 17 branches of industrial sectors. Since some data for European countries (taken from Eurostat's *Structure of Earnings* (SOE)) follow NACE categorization, these data were converted into ISIC code using Table 3.3 in OECD's *ISDB*. The industrial coverage used in this paper is described in Table A.1.

Labor input factors for non-European countries were disaggregated into seven categories according to ISCO-1968 which included professional/technical workers (code 0/1), administrative/managerial workers (2), clerical workers (3), sales workers (4), service workers (5), agricultural workers (6) and production workers (7/8/9). For European countries, labor were disaggregated into production workers and non-production workers. Non-production workers consisted of top management executive, other senior executives, assistants, clerical and supervisors. The labor categorization used in this paper (Euro I and Euro II) and their concordance with ISCO and SOC classifications are in Table A.2.

A.1.2 Technology

The technology matrices consist of two parts: direct input matrix (**A**: factor by industry) and input-output matrix (**B**: industry by industry).

Direct Input Matrix

This measures how much labor and capital is actually employed in each industry at a given point of time. The disaggregated occupational distribution of labor were taken from the table of *Economically Active Population by Occupation* in KILO's *Statistical Yearbook of Labor Force (1945-1989)*. However in this table, the manufacturing sector was not disaggregated at the sectoral level. To obtain the occupational distribution of labor in each sector of manufacturing, we relied on each country's census of population data for non-European countries[1] and on the SOE for Euro-

[1]For US and Korea, the data are available from 1980 *Census of Population* in each country. But for Canada, the occupational distribution in disaggregated manufacturing industries are available only from 1996 census. Thus we assume that the ratio of occupational distribution to total manufacturing workers does not change very much over time and use the information from 1996 census

pean countries. The numbers of workers in each occupation in each manufacturing sector collected in this way was rescaled so that the total numbers of occupational workers in manufacturing equal to ILO's *Yearbook*.

Data on net capital stocks (at the sectoral level) were not directly available for the various countries in our sample. Measures of net capital stock had therefore be constructed instead.[2] Our measure of the net stock of capital was constructed as follows: We computed first the initial net capital stock in each industry in 1970. This was done by taking the *aggregate* net capital stock in 1970 from *Penn World Table* and the gross capital stock of each industry in 1970 from the ISDB. Then, the net capital stock in each industry was computed by distributing the total net capital stock number into each industry using the industrial ratio in ISDB. Second, data on annual gross fixed capital formation in each industry during 1971-1980 were taken from the ISDB. (Since ISDB does not have data on Korea, we obtained this data from National Account Department of the Bank of Korea.) Taking the initial disaggregated net capital stock and each year's disaggregated capital formation data, we used Perpetual Inventory Method to compute net capital stock in each industry in 1980. The test results reported in Section 1.4 used depreciation rate of 5%. To check sensitivity, we repeated the same procedure with depreciation rates of 3% and 10%. The results were not sensitive to these changes.

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[2]Measuring capital stock in each industry is an important issue not only because it is a component of direct input matrix but also because it affects directly calculated the rate of return to capital.

Input-Output (I/O) Matrix (Indirect Input Matrix)

The entries in this matrix represent the amount of intermediate inputs that a sector purchases from other sectors to produce one unit of output. OECD's *I/O Database* provides three sets of Input-Output matrices for each country. The first is the 'Domestic I/O matrix' which shows the usage of domestically produced intermediate goods in each sector. The second is the 'Imported I/O matrix' which measures how many intermediate goods are imported from abroad in each sector. Finally, we have the total I/O matrix' is a simple summation of domestic and imported I/O matrix.

Given Staiger's (1986) proposed modification the factor content calculations suggested in Helpman (1984), the domestic I/O matrix (which does include the factor content of traded intermediate goods) is a more appropriate choice rather than the total I/O matrix. To see the underlying logic of his argument, consider the following simple three country - four commodity case. Good 1 and good 2 are final goods which use good 3 and good 4 as intermediate goods. In particular, to produce one unit of good 1, we need α unit of good 3 and β unit of good 4. Also assume that unit labor requirement is one both for good 3 and 4. Country A, B and C produce good 1, 2 and 3, respectively and good 4 is produced both by country A and B. Now, suppose country A export one unit of good 1 to country B. Then countryA's production cost will be

$$w^A\beta + w^C\alpha$$

If this were produced in country B, the production cost will be

$$w^B\beta + w^C\alpha$$

For country A to be an exporter of good 1,

$$w^A\beta + w^C\alpha \leq w^B\beta + w^C\alpha$$

or

$$(w^B - w^A)\beta \geq 0$$

This last expression is nothing but what we derived in Section 2.2. Note that in the end, the relevant input-output coefficient is not that of imported intermediate good (α) but that of domestically produced intermediate good (β).

A.1.3 Bilateral Trade

The manufacturing sector's bilateral trade data were directly obtained from OECD Bilateral Trade Database for each pair of countries in our sample. This data provide the bilateral trade flows based on ISIC categorization, so readily conformable with technology matrix constructed above. The bilateral trade for non-manufacturing sectors were not available. So, as was done by Davis and Weinstein (1998), bilateral imports of non-manufacturing sectors were set equal to the share of manufacturing imports from that country times total non-manufacturing imports in that sector, where total non-manufacturing imports were taken from OECD I/O Database.

A.1.4 Factor Prices

The construction of factor price data were described in Section 1.3 in more detail, so only brief description is provided here. For capital, the *ex-post* rental rate of capital were calculated by dividing Operational Surplus from OECD's Annual National Account Database by total capital stock from OECD's International Sectoral

Database. The occupational wage rate were taken from Census of Population for each non-European countries and Structure of Earnings for European countries. For the purpose of international compatibility, these data were modified as described in Section 1.3.

A.2 Hicks-neutral Technology Differences

An attractive feature of the framework described above is that it relaxes a number of unrealistic assumptions regarding factor prices and consumer preferences that have traditionally been made in the empirical literature in this area. However, as we have already noted, one rather restrictive assumption remains: identical CRS technologies across countries. To relax this somewhat, we allow for Hicks-neutral factor efficiency differences across countries (just as in Trefler (1993, 1995)). The derivation of the restrictions analogous to (1.7)-(1.9) is straightforward:

Suppose that all input factors in country c' are more productive than those in country c by the factor of λ ($\lambda > 0$). Then, equation (1.4) becomes

$$\begin{aligned} \mathbf{p}(\mathbf{Q}^{c'} + \mathbf{T}^{c'c}) &\leq \mathbf{\Pi}(\mathbf{p}, \mathbf{V}^{c'} + \frac{1}{\lambda}\mathbf{T}_V^{c'c}) \\ &\leq \mathbf{\Pi}(\mathbf{p}, \mathbf{V}^{c'}) + \mathbf{\Pi}_V(\mathbf{p}, \mathbf{V}^{c'})\frac{1}{\lambda}\mathbf{T}_V^{c'c} \\ &= \mathbf{p}\mathbf{Q}^{c'} + \frac{(\mathbf{w}^{c'})}{\lambda}\mathbf{T}_V^{c'c} \end{aligned} \tag{A.1}$$

because now country c' could do better than country c (in terms of output) even with only $\frac{1}{\lambda}\mathbf{T}_V^{c'c}$. Applying the zero profit condition in country c ($\mathbf{p}\mathbf{T}^{c'c} = (\mathbf{w}^c)\mathbf{T}_V^{c'c}$), we have the following equation (corresponding to equation (1.7) in the previous section):

$$(\frac{\mathbf{w}^{c'}}{\lambda} - \mathbf{w}^c)\mathbf{T}_V^{c'c} \geq 0 \tag{A.2}$$

In general, if λ^i is the Hicks-neutral technology parameter describing factor efficiency levels in country i relative to some benchmark country, (1.7)-(1.9) would be rewritten as

$$\left(\frac{\mathbf{w}^{c'}}{\lambda^{c'}} - \frac{\mathbf{w}^{c}}{\lambda^{c}}\right)\mathbf{T}_V^{c'c} \geq 0 \tag{A.3}$$

$$\left(\frac{\mathbf{w}^{c}}{\lambda^{c}} - \frac{\mathbf{w}^{c'}}{\lambda^{c'}}\right)\mathbf{T}_V^{cc'} \geq 0 \tag{A.4}$$

$$\left(\frac{\mathbf{w}^{c'}}{\lambda^{c'}} - \frac{\mathbf{w}^{c}}{\lambda^{c}}\right)(\mathbf{T}_V^{c'c} - \mathbf{T}_V^{cc'}) \geq 0 \tag{A.5}$$

Table A.1: Seventeen Industries and its Concordance with ISIC and NACE

Description	ISIC Code	NACE R6/R25
1. Agriculture, Hunting, Forestry and Fishing	1	01
2. Mining and Quarrying	2	12,14
3. Food, Beverages and Tobacco	31	36
4. Textiles, Apparel and Leather	32	42
5. Wood Products	33	48
6. Paper, Paper Products and Printing	34	47
7. Chemical Products	35	17,49
8. Non-metallic Mineral Products	36	15
9. Basic Metal Industries	37	13
10. Fabricated Metal Products and Machinery	38	19,21,23,25,28
11. Other Manufacturing	39	48
12. Electricity, Gas and Water	4	06
13. Construction	5	53
14. Wholesale and Retail Trade, Restaurants and Hotels	6	56,59
15. Transport, Storage and Communication	7	61,63,65,67
16. Finance, Insurance, Real Estate and Business Services	8	69A
17. Community, Social and Personal Services	9	74

Table A.2: Concordance of Labor Categories

Euro I	Euro II	ISCO-1968 (Non-European Countries)	Structure of Earnings (European Countries)
production	production	service (5) agricultural (6) production (7/8/9)	manual workers
non-production	managerial	administrative / managerial (2)	top management executives other senior executives
	clerical	clerical (3)	clerical
	others	professional / technical (0/1) sales (4)	assistants supervisors

Appendix B

Appendix to Chapter Two

B.1 Data Description

Data coverage is described in Table B.1. The main data sets used in this paper are recently published series of OECD database which include STAN (Structural Analysis) Database, IO (Input-output) Database, BTD (Bilateral Trade) Database and ANBERD (Analytical Business Enterprise Research and Development) Database. All of these data sets contain disaggregated industrial data according to ISIC Rev 2 for the period of 1973-1991. Other OECD datasets such as ISDB (Industrial Structure Database) and ANA (Annual National Account) Database also used to get hours of work and implicit GDP deflator.

B.1.1 Total Factor Productivity

The formula for TFP calculation is given in the left-hand side of equation (2.5). In order to calculate this at industry level, we need value added, labor, capital stock and labor share for each industry. The value added data are taken from STAN Database at current prices and are converted into 1990 prices using implicit GDP deflator. The "number of engagements" variable in STAN Database was used for labor. This number was adjusted by hours of work data from ISDB. The labor share data was constructed by dividing labor compensation by value added data from STAN. Since the labor share data calculated in this way exceed 1 in many cases at industrial level (due to industrial recession etc.), we use the labor share of total manufacturing of each country averaged over the time period covered by our data.

Capital stock data is not directly available in the OECD data sets. Instead, gross fixed capital formation variable in STAN was used to calculate physical capital stock. The gross fixed capital formation variable was converted into 1990 prices using investment deflator from Penn World Table. Then, the perpetual inventory method was applied, i.e., $K_t = I_t + (1 - \delta_K)K_{t-1}$ where I_t and K_t are gross fixed capital formation and physical capital stock at time t, respectively. The depreciation rate δ_K is assumed to be 10%. The benchmark value of physical capital stock is estimated by $I_0/(\delta_K + g_I)$ where g_I is the average annual growth rate of gross fixed capital formation for available time period.

B.1.2 R&D Capital Stock

The OECD ANBERD Dataset contains data on R&D expenditure at industrial level from 1973 to 1991 at current prices. Since price deflators (in an R&D context) are not available, we used the implicit GDP deflator to convert them into 1990 constant prices. Then, the R&D capital stock series is constructed by the perpetual inventory method by $R_t = RE_t + (1 - \delta_R)R_{t-1}$ where RE_t and R_t are R&D expenditure and R&D capital stock at time t, respectively. The depreciation rate δ_R is assumed to be

10% as in Coe and Helpman (1995). The initial value was set to be $RE_0/(\delta_R + g_R)$ where g_R is the average annual growth rate of R&D expenditure.

B.1.3 Weighting Coefficients

The OECD Input-Output Database was used to calculate our weighting coefficients. Since these IO tables are not reported annually and Italy has only 1985 IO table, we used the following IO table for each country: Canada 1986, France 1985, Germany 1986, Italy 1985 Japan 1985, Netherlands 1986, UK 1984 and US 1985. Each country's IO table breaks down inter-industrial transaction flows of goods and services into those that are domestically-produced and those that are imported and into intermediate and capital goods. Thus this database consists of the following four tables for each country.

- domestic intermediate goods flows matrix (DG)
- imported intermediate goods flows matrix (MG)
- domestically-sourced investment goods flows (DI)
- imported investment goods flows matrix (MI)

We first combine two domestic matrix (DG + DI = DIO) and two import matrix (MG + MI = MIO) since both intermediate flows and investment flows are recognized as important channel of R&D spillovers in the literature. Then, the domestic interindustry weighting coefficients (ω_{kij}) were calculated using the DIO matrix and the interindustry weighting coefficients for imported intermediate goods (μ_{kij}) were

Table B.1: Data Coverage

Eight Countries	Thirteen Industries	
	ISIC Code	Description
Canada	31	Food, Beverages and Tobacco
France	32	Textiles, Apparel and Leathery
Germany	33	Wood Products and Furniture
Italy	34	Paper, Paper Products and Printing
Japan	351+352	Chemicals
Netherlands	353+354	Petroleum Refineries and Products
United Kingdom	355+356	Rubber and Plastic Products
United States	36	Non-Metallic Mineral Products
	37	Basic Metal Industries
	381	Metal Products
	382+385	Non-Electrical Machinery and Professional Goods
	383	Electrical Machinery
	384	Transport Equipment

calculated using the MIO matrix.[1] See the main text for the exact formulas used for construction of these weighting coefficients.

Finally, in calculating same industry's R&D capital stock in the foreign country, bilateral import share data is needed at the industrial level. This data is taken directly from OECD BTD Database.

[1]The typical elements of DIO matrix and MIO matrix are denoted in the main text by d_{kij} and m_{kij}, respectively.

B.2 Derivation of Equation (2.13)

For simplicity, we write down the closed economy version of the estimation equation without time subscript.

$$\ln TFP_i = \theta + \beta_1 \ln RD_i + \beta_2 \ln \overline{RD}_i + \epsilon_i$$

Then, the parameter β_2 represents the elasticity of industry i's TFP with respect to its domestic-outside industries' effective R&D capital stock, since

$$\frac{\partial \ln TFP_i}{\partial \ln \overline{RD}_i} = \beta_2$$

Now, by definition of domestic-outside industries' effective R&D capital stock, we know that

$$\overline{RD}_i = \sum_{k \neq i}^{p} \omega_{ki} R_k \quad \text{or} \quad \ln \overline{RD}_i = \ln(\sum_{k \neq i}^{p} \omega_{ki} R_k)$$

Then, the elasticity of industry i's TFP with respect to industry k's actual R&D capital stock can be obtained by

$$\begin{aligned} \frac{\partial \ln TFP_i}{\partial \ln R_k} &= \frac{\partial \ln TFP_i}{\partial \ln \overline{RD}_i} \cdot \frac{\partial \ln \overline{RD}_i}{\partial R_k} \cdot (\frac{\partial \ln R_k}{\partial R_k})^{-1} \\ &= \beta_2 \cdot \frac{\omega_{ki}}{\sum_{k \neq i}^{p} \omega_{ki} R_k} \cdot R_k \\ &= \beta_2 \cdot \frac{\omega_{ki} R_k}{\sum_{k \neq i}^{p} \omega_{ki} R_k} \end{aligned}$$

which is strictly less than β_2.

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