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ESTIMATION OF CROSS-COUNTRY DIFFERENCES IN INDUSTRY PRODUCTION FUNCTIONS

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ABSTRACT

Many economists and policy makers are concerned about international differences in technology and labor quality, correctly seeing these issues as crucial to long term growth in living standards. Typically, international trade economists assume that technological knowledge is the same in all countries, and that production processes exhibit constant returns to scale. An equivalent way of stating this assumption is that total factor productivity (TFP) for each industry is the same in every country. This paper is a contribution to a growing body of work which casts doubt on this hypothesis, finding large and persistent TFP differences across countries. The paper uses a new data set on prices, inputs, and outputs for a group of industrialized countries in the 1980s. In addition to calculating industry-specific TFP indexes over time and across countries, the paper uses panel data econometric techniques to examine the sources of the observed large TFP differences across countries. Two hypotheses are examined to account for TFP differences: constant returns to scale production with country-specific technological differences, and industry-level scale economies with identical technology in each country. The data support the constant returns/different technology hypothesis over the increasing returns/same technology hypothesis.

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Estimation of Cross-Country

Differences in Industry Production Functions

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1. Introduction

Two fundamental assumptions in neoclassical trade theory are that technological knowledge is the same in all countries, and that production processes exhibit constant returns to scale. An equivalent way of stating this assumption is that total factor productivity (TFP) for each industry is the same in every country: a given level of inputs will produce the same amount of output in each country. If this is the case, then production sets differ across countries only because of differences in factor endowments. Recent work by Harrigan (1995), however, shows that there are systematic differences across countries in industry outputs that can not be explained by differences in factor endowments. While there are many possible explanations for this result, one such explanation is that technology is not the same across countries. This is a hypothesis which has gained greater attention from international economists recently, including Trefler (1993, 1995), Dollar and Wolff (1993) and Harrigan (1997). If technology is not the same across countries, then much of the theoretical work in neoclassical trade theory is irrelevant to applied research on cross-country comparisons, and much of the applied research that assumes identical

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technology (for example, many applied general equilibrium models and factor endowment regressions) is misspecified.

One important possibility, however, is that TFP differences are the result of a mismatch between the theory of TFP comparisons and the technological and measurement processes which generate the data. For example, if there are increasing returns to scale at the level of national industries, then countries with larger industry outputs will have higher measured TFP even if technology is identical. If there is imperfect competition in output or input markets, then labor's share of total factor payments need not correspond to labor's share of total costs. If there is substantial measurement error in inputs and/or outputs, then TFP may also appear to be substantially different even if the underlying technology is the same. This paper investigates the possibility that returns to scale and/or imperfect competition effects bias TFP comparisons.

In this paper, I estimate cross-country technology differences using two approaches. I compute TFP indexes using a panel of data on value added, capital stocks, and employment for eleven OECD countries during the 1980's. This data set combines newly available data from the OECD and the U.S. Bureau of Economic Analysis. Using the same data, I directly estimate cross-country differences in industry production functions. The econometric results are used to draw inferences about technological differences which are compared to the direct calculations of TFP .

There are two general types of studies that have calculated international TFP differentials: studies of value added and studies of gross output. Within this breakdown, there are studies which vary in their level of disaggregation and their country coverage. There are a number of studies of <u>growth</u> in TFP which are not reviewed here, since they are not directly relevant to the question of the level of TFP across countries[1].

Among the studies which calculate TFP using a value added output measure are Dollar and Wolff (1993), Dollar, Wolff and Baumol (1988), Maskus (1991), van Ark (1993), and van Ark and Pilat (1993). The first three of these use overall GDP price levels to deflate sectoral outputs. This introduces a distortion to the extent that relative prices differ across countries, and Harrigan (1996) shows that this distortion is large enough to substantively change the results of TFP comparisons. The two closely related studies by van Ark (1993) and van Ark and Pilat (1993) deflate value added by a price index which is constructed by direct comparisons of output prices at the wholesale level rather than using GDP price levels. Unfortunately, this theoretically superior procedure is compromised by the very small number of matches across countries for particular products (see the discussion by Jorgenson following van Ark and Pilat 1993). In addition, the van Ark (1993) and van Ark and Pilat (1993) studies include only a small number of countries and years.

The second class of studies of TFP uses data on gross output, and deflates all inputs (capital, labor, materials, energy, etc) in a symmetric way. This procedure was pioneered by Jorgenson and various coauthors, and is undoubtedly the most theoretically appealing and least restrictive method of making productivity comparisons (see Jorgenson (1990) for a comprehensive introduction to the methodology). Because of the very stringent data requirements needed for the Jorgenson procedure, however, there have been only two studies applying this method and they have compared only two countries, the United States and Japan.

[1] Studies of sectoral TFP growth include Costello (1993) and Bernard and Jones (1996a, 1996b).

The current paper extends the literature in three ways. First, to avoid assuming that relative prices do not vary across countries I construct estimates of sector-specific price levels. Second, I use data on a broad sample of OECD countries over ten years. Lastly, I use both index number theory and cross-country econometric analysis to characterize the extent of TFP differences[2].

2. Data

The data and measurement issues involved in making international comparisons of industries are discussed extensively in a companion paper to this one (Harrigan (1996)). In this section I describe some of the methods and conclusions of that paper.

2.1 Real Output

Cross-country comparisons require data on outputs, inputs and prices. The OECD has recently compiled data on nominal output, valued added, employment, and gross fixed capital formation (GFCF) from a number of existing data sources to form a single internally consistent source for disaggregated cross-country comparisons[3].

Making the OECD data internationally comparable requires currency conversion, and this is the most problematic part of any international comparison. Using purchasing power parity (PPP) GDP deflators is the most common procedure, but this biases industry level comparisons since it implicitly assumes that there are no relative price differences across countries. Some of the problems of using GDP PPPs can be mitigated by using the component deflators reported in the

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[2] See Harrigan (1996) for a more detailed summary and critique of previous research on international sectoral TFP comparisons.

[3] The data set is called STAN (STructural ANalysis); see OECD 1992a.

OECD documentation of the construction of the overall GDP PPPs (Ward 1985, OECD 1987, and OECD 1992b). This paper constructs price levels for machinery and equipment using this disaggregated data[4]. Expressed as a percentage of the overall GDP deflator price levels, the constructed price levels vary widely across countries: the standard deviation across countries is on the order of 20 percentage points, with a range of around 65 percentage points (see Table 1 in Harrigan (1996)). If a country's price level is high, it is because a standardized unit of output is more expensive in that country than in the US; it does not mean that output in that country is of higher quality, since the price index ostensibly compares like goods in the countries being compared. The standardized unit of output being compared is meant to be representative of the OECD as a whole, so the choice of the dollar as a standard for purposes of cross country comparisons is inconsequential.

The above procedure converts nominal domestic currency magnitudes into units of nominal US dollars sufficient to purchase a standardized basket of goods. To make these dollar magnitudes comparable over time, value added is deflated using industry price indexes from the Bureau of Economic Analysis.

2.2 Capital

The OECD data reports industry investment flows in current own-currency values. I convert industry investment into U.S. dollars using the overall investment price levels from Summers and Heston (1991), and the flows are then converted into constant dollars using the implicit deflator for US fixed non-residential investment from the National Income and Product Accounts, various years.

[4] This approach is also used by Hooper and Larin (1989).

Given the series on real investment, the capital stock is a function of past investment flows. The choice of function is both important and somewhat arbitrary, since it is not feasible to gather information on useful asset lives and depreciation patterns across industries and countries. I (rather uncomfortably) follow many previous researchers and construct the capital stock as a distributed lag of past investment flows:

$$k_{cjt} = \sum_{n=1}^{T} (1-\delta)^{n-1} i_{cj,t-n} \tag{1}$$

where k_{cjt} is the capital stock of industry j in country c at the beginning of year t, $\delta < 1$ is the discount factor, and i is real investment during year t. Note that the capital stock in year t does not include year t investment, but only up through year t-1. In this paper, because I only have investment going back to 1970, I use $\delta = 0.15$ and T = 10. If the actual useful life of a capital good is 20 years, this amounts to dropping about 10% of the total weight used in constructing the "true" capital stock.

An alternative method is to use the so-called delayed linear scrapping rule: a newly purchased capital good is added to the capital stock, and after a period of S years a constant proportion 1/(M+1) is scrapped each year:

$$k_{cjt} = \sum_{n=1}^{S} i_{cj,t-n} + \sum_{n=S+1}^{S+M} i_{cj,t-n} \cdot \left[1 - \frac{n-S}{M+1}\right]$$

This is a formula used by many national statistical agencies, as well as by the OECD in it's Intersectoral Database for international comparisons (OECD, 1996).

With S=3 and M= 7, the resulting capital stock estimates are extremely highly correlated with the capital stocks constructed using equation (1): the minimum within-industry correlation is 0.9992. Of course, there are other plausible parameter choices which would yield different capital stock estimates, but given the short sample available, all would be highly correlated since they would all give high weight to recent investments, quickly declining weight to investments more than a few years old, and zero weight to investments more than 10 years old.

2.2 Labor

Labor is derived from industry employment figures in the STAN data. Because employment is an imperfect indicator of labor input, two adjustments are made to these data. First, the employment data are converted into 40-hour work week equivalents using average hours worked in manufacturing. Second, the data are disaggregated into three occupational categories (professional/technical, managerial, and other) using the proportions of each occupation in manufacturing[5]. The occupational categories are aggregated into total labor l using a translog index:

$$l = l_1^{\alpha_1} l_2^{\alpha_2} l_3^{\alpha_3} \tag{2}$$

where the subscripts refer to the three occupational categories and country-industry-year subscripts are omitted for readability. The weights α_1, α_2, and α_3 sum to unity and are constructed from each occupation's share in total labor cost. Analogously to the total cost shares used in the TFP index introduced below, I use the following weights in constructing the index of labor for country c in year t:

$$\alpha_m = (s_m + \bar{s}_m)/2$$

[5] Hours worked and occupational data are both from the Year Book of Labour Statistics, various years.

where s_m is the share of occupation m in total cost for a particular country-industry-year observation and $\bar{s}_m$ is the arithmetic mean of s_m across observations. Construction of the labor cost shares s_m requires data on wages. Unfortunately, internationally comparable wage data that is disaggregated by occupation is unavailable. The approach used here is to assume that the occupational wage differentials in the United States are the same as in other countries. These wage differentials can be constructed from data in the Bureau of Labor Statistics (BLS) Handbook of Labor Statistics for the years 1983 to 1988 (BLS 1989, page 163-168)[6]. Denote the wage of occupation m as w_m and the occupational wage differentials as β_m, with the normalization that the lowest paid occupation is occupation 1 and $\beta_1 = 1$. Substituting $w_m = \beta_m w_1$ into the definition of total labor cost $= \sum_m w_m \cdot l_m$, and solving for w_1 it is the case that

$$w_1 = \sum_m w_m \cdot l_m / \sum_m \beta_m \cdot l_m$$

Given this constructed numeraire wage, the wage shares follow immediately as

$$s_m = w_m l_m / \sum_j w_j \cdot l_j = \beta_m l_m / \sum_j \beta_j \cdot l_j \qquad m = 1,\ldots,L.$$

3. Total Factor Productivity

In this section I report relative TFP levels calculated from the above described data on value added y, employment l, and capital stocks k. The comparison of TFP between two countries b and c asks the question: how much output could country b produce using country c's inputs, or vice versa? Assume that value added can be modeled as a function of the capital stock and employment, and that these inputs are measured perfectly and in the same units for each observation. For a

[6] I use the 1983 differentials for 1980-82 and the 1988 differentials for 1989-90. This is a small distortion since these differentials change slowly over time.

particular industry in country c , write real value added y_c as a constant returns to scale function of the real capital stock k_c and the level of employment l_c:

$$y_c = f_c(k_c, l_c) = f_c(x_c)$$

Now define the distance function $D_b(y_c, x_c)$ as follows:

$$D_b(y_c, x_c) = \mathrm{Min}_\delta \{ \delta \in \mathbb{R}^1_+ : f_b(\delta x_c) \geq y_c \}$$

With this definition, $D_b x_c$ is the smallest input bundle capable of producing y_c using the technology in country b. $D_c(y_b, x_b)$ is defined analogously. Note that in general it need not be the case that $D_c = 1/D_b$, so that the calculated distance between the technologies of two countries b and c depends on the value added function used for the comparison. Further complications arise in making multilateral comparisons within a panel of countries since the choice of base country and year will affect the conclusions. As a solution to this index number problem, suppose that each country's value added function is translog with identical second-order terms, so that the value added function of country c can be written as

$$\ln y_c = \alpha_{0c} + \alpha_{1c} \ln l_c + \alpha_{2c} \ln k_c + \alpha_3 (\ln l_c)^2 + \alpha_4 (\ln k_c)^2 + \alpha_5 (\ln l_c \cdot \ln k_c)$$

where constant returns to scale requires $\alpha_{1c} + \alpha_{2c} = 1$ and $2\alpha_3 + \alpha_5 = 2\alpha_4 + \alpha_5 = 0$. Under the additional assumptions that producers are cost-minimizers and price takers in input markets, Caves, Christensen and Diewert (1982) show that the geometric mean of the two distance functions for any two countries b and c gives the TFP index

$$TFP_{cd} = \frac{y_c}{y_d}\left(\frac{\bar{l}}{l_c}\right)^{\sigma_c}\left(\frac{\bar{k}}{k_c}\right)^{1-\sigma_c}\left(\frac{l_d}{\bar{l}}\right)^{\sigma_d}\left(\frac{k_d}{\bar{k}}\right)^{1-\sigma_d} \tag{3}$$

where a bar denotes an average over all the observations in the sample and $\sigma_j = (s_j + \bar{s})/2$, where s_j is labor's share in total cost in observation j [7]. To interpret (3), notice that if the value added function is Cobb-Douglas, then the labor shares are constant and (3) reduces to the Cobb-Douglas index:

$$TFP_{cd} = \frac{y_c}{y_d}\left(\frac{l_d}{l_c}\right)^{s}\left(\frac{k_d}{k_c}\right)^{1-s}$$

The index (3) is superlative, meaning that it is exact for the flexible translog functional form[8]. Furthermore, (3) is transitive:

$$TFP_{bd} = TFP_{bc} \cdot TFP_{cd}$$

(4)

which makes the choice of base country and year inconsequential[9].

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[7] It is possible to enter the three labor occupational categories separately in a version of (3) rather than first aggregating them using equation (2). The difference in the implicit weights given to the labor categories is second order, and the difference in the calculated levels of TFP appear only in the fourth digit or later.

[8] An index number formula is said to be "exact" for a particular functional form if it equals the Fisher "ideal" index for that functional form, where the "ideal" index is the geometric mean of a Paasche and a Laspeyres index. An index is said to be "superlative" if it is exact for a flexible functional form such as the translog. See Diewert (1976).

[9] Diewert (1992) is a good survey of different TFP indices and the often subtle issues involved in choosing among them. In a recent paper, Bernard and Jones (1996b) note that the index used by Dollar and Wolff (1993) is unit dependent, and they propose a new "TTP" index as a replacement for the Caves-Christensen-Diewert (CCD) index used in the current paper. Their criticism of the CCD index (pg. 1232) is very confused. They claim that the CCD index "ignores

A major difficulty in implementing a TFP comparison is volatility in the labor shares s_j, which is suggestive of measurement error. Under the assumptions about technology and input market behavior used to derive (3), labor's share in total cost is equal to the elasticity of output with respect to labor, so that

$$s_c = \alpha_{1c} + \alpha_5 \ln (k_c/l_c) \quad (5)$$

The cost shares in the raw data are very volatile, and in many cases exceed one. In the results reported below, I use a smoothing procedure based on equation (5) to generate the cost shares used in constructing the TFP index. For each industry, I estimate the following regression by OLS over all time periods t and countries c:

$$s_{ct} = \beta_{0c} + \beta_1 \ln (k_{ct}/l_{ct}) + \epsilon_{ct}$$

I use the fitted values from this regression as the labor cost shares in constructing the reported TFP indexes. In cases where the fitted values exceed one I use the sample mean for the industry. For shipbuilding and repairing, the sample mean for labor's share exceeds one, so I use the sample mean for labor's share in all machinery. Of course, this suggests that the TFP index for shipbuilding should be regarded with great skepticism.

Table 1 reports relative TFP[10]. For each industry, the country and year of comparison is the US level in 1987; this year was chosen because it is a year with

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differences in factor exponents", which is simply false, and they claim that in, for example, US-Japan comparisons "the rank comparison may depend on whether one uses the Japanese or the U.S. factor share", which is unintelligible since the CCD index uses an average of the country's factor shares rather than one or the other. This criticism does apply to their own TTP index, which they acknowledge. In addition, the TTP index is based on a restricted form of the translog with second order terms set identically equal to zero, so their rejection of the translog's implications for time-series variation in factor shares applies *a fortiori* to their own index.

[10] Harrigan (1996) reports a more complete version of Table 1; some results are omitted here in the interests of brevity.

complete US observations across industries, and because it represents a year of approximately full employment in the US. The first observation is that few of the entries are close to 100, meaning that for most countries and years the level of TFP is different from the US level in 1987. This general point accords with previous research, and casts doubt on the notion that technology is the same across the sampled countries. Second, there is a great degree of volatility over time within countries, some of which seems to be attributable to business cycle effects; for example, US TFP declines during the 1982-83 recession, and increases thereafter[11].

Careful scrutiny of Table 1 induces a deep suspicion about data problems. For example,

1. Australian TFP in each industry plummets between 1982 and 1983, a result due to a big jump in measured employment.
2. Italian TFP in motor vehicles nearly quadruples from 1987 to 1988.
3. US TFP in electrical machinery more than doubles from 1986 to 1987.

To the extent that these data problems come from random mis-measurement of outputs, they will not bias the econometric results reported below. To the extent that there is non-random measurement error (e.g. correlated across observations) or there is measurement error in inputs, the econometric results will be biased.

Table 2 offers a summary of the TFP results reported in Table 1. For each industry, the log of TFP is regressed on country fixed effects and a time trend. The US is the excluded fixed effect, so the exponential of the country fixed effects are average TFP relative to the US during the sample period, after detrending. The elements of Table 2 are these exponentiated estimated fixed effects. For each

[11] These cyclical effects are why the numbers are presented relative to the US level in 1987; year by year comparisons to the US are uninformative because they are dominated by differences across countries in the stage of the business cycle.

industry, proportionate differences outside the approximate interval (0.95,1.05) are statistically significantly different from 1.0 at the 5% confidence level; the only exception is the "other transport equipment" industry, where because of the small sample size none of the proportions is significantly different from 1.0

Table 2 makes it clear that the US was either the leader or co-leader in TFP during the 1980's in six of the eight industries. The US trailed badly only in electrical machinery, and was tied for second with Japan in shipbuilding. In motor vehicles, the US and Japan had a TFP lead of 20-25% over a group of countries including Canada, Germany, and Italy. The US was the clear leader in office and computing equipment and (surprisingly?) in radio, TV, and communications equipment.

Table 3 summarizes cross-industry TFP using a version of the multilateral TFP index of equation (3). The index number formula used in Table 3 weights sectoral outputs relative to the mean using revenue shares, and expresses this quantity relative to an index of total capital and labor used in all sectors, where inputs are weighted using cost shares. The formula for comparing country-year b relative to country-year c is

$$TFP_{bc} = \left[\prod_{j=1}^{N} \left(\frac{y_{bj}}{\bar{y}_j} \right)^{\rho_{bj}} \left(\frac{\bar{y}_j}{y_{cj}} \right)^{\rho_{cj}} \right] \left(\frac{\bar{l}}{l_b} \right)^{\sigma_b} \left(\frac{\bar{k}}{k_b} \right)^{1-\sigma_b} \left(\frac{l_c}{\bar{l}} \right)^{\sigma_c} \left(\frac{k_c}{\bar{k}} \right)^{1-\sigma_c} \tag{6}$$

where

y_{cj} = real value added in country c by sector j

$\rho_{cj} = (r_{cj} + \bar{r}_j)/2$, where r_{cj} is the share of total value added in country c accounted for by sector j.

l_c = total labor employed in country c (that is, summed over all N sectors)

k_c = total capital stock in country c (that is, summed over all N sectors)

$\sigma_c = (s_c + \bar{s})/2$, where s_c is labor's share in total cost in country c.

Overbars indicate averages over all the observations in the sample. The subscripts b and c can refer to any two distinct observations, such as two different countries during the same year, two different countries in different years, or the same country in different years. As with equation (3), equation (6) is easiest to understand in the Cobb-Douglas case, when the revenue and cost shares are the same across observations, in which case (6) reduces to

$$TFP_{bc} = \left[\prod_{j=1}^{N}\left(\frac{y_{bj}}{y_{cj}}\right)^{r_j}\right]\left(\frac{l_c}{l_b}\right)^{s}\left(\frac{k_c}{k_b}\right)^{1-s}$$

The index (6) used in Table 3 has all the same desirable properties as the industry-by-industry index (3) used in Table 1: it is superlative and transitive.

One practical problem with applying (6) is that it is undefined if there are missing observations for a particular industry. Since there are many holes in the data, this makes it impossible to compare many observations. In constructing Table 3, I apply (6) using data on all industries except Aircraft and Other Transport Equipment. Excluding these two industries allows calculation of cross-industry TFP for eight countries on the remaining six industries. Excluding aircraft will lower US relative TFP in machinery and equipment, since the US has a large aircraft industry which has a substantial TFP advantage over other countries.

The information in Table 3 is presented in two ways. In Panel A, each observation is expressed relative to the US in 1987; Panel B presents year by year comparisons relative to the US. Figures 1 and 3 illustrate the data in Panels A and B respectively. In the late 1980s, the United States and Japan were the co-leaders in TFP among the large countries[12]. A group of four countries (Germany, Italy, Canada and Norway) were 10-20% points behind the US and Japan. Britain, at 60-70% of US TFP, is the clear laggard among the eight countries in the table. A surprise is that Finland is roughly equal to the US and Japan in TFP. A clue to this is apparent from Table 2: Finland's TFP in electrical machinery is very high, and it happens that Finland has a very high share of value added in this sector so that the sector gets large weight in the overall TFP calculation. Panel A of Table 3 shows that of the seven countries with at least nine years of data, only Canada and Japan did not see substantial TFP growth from the early to the late 1980s; United States TFP grew by over 20%. A comparison of Tables 1, 2, and 3 is instructive: the overall numbers in Table 3 mask considerable sectoral TFP differences in Table 2, while the decade-average TFP differences in Table 2 obscure the substantial year to year variations in TFP that are apparent in Tables 1 and 3.

As noted above, one difficulty in interpreting the TFP numbers is that TFP is procyclical. A simple way to adjust for this is to scale sectoral output by a measure of the GDP gap. Table 4 reports TFP where actual output has been replaced by output multiplied by the ratio of potential to actual GDP; in recession years this amounts to attributing greater potential output to a sector than the amount actually produced. Figures 2 and 4 illustrate the two panels of Table 4. The pattern of

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[12] In Jorgenson, Kuroda and Nishimizu (1987), the authors do not report the levels of relative TFP, but they do report that Japan trailed the US in machinery and equipment in 1979, although they expected Japan to close the gap with the US in the near future (pg. 26). Jorgenson and Kuroda (1990) updates the earlier study, and reports that by the mid-1980's Japan had industry TFP that was equal to or greater than US TFP in many machinery sectors. Their results are quite consistent with the results reported here, which provides some grounds for hoping that the results of value added and gross output TFP comparisons might generally be comparable.

relative TFP is not greatly affected by this adjustment, as can be seen most clearly by comparing Figure 1 with Figure 2, or Figure 3 with Figure 4.

All four tables suggest that the three largest economies (US, Japan, and Germany) generally have the best TFP performance. This is consistent with industry-level economies of scale being an important determinant of TFP[13]. Industry-level scale economies are not the sort of scale economies often considered in recent trade models, such as the monopolistic competition trade model summarized by Helpman and Krugman (1985, Chapter 5-7), where industry production functions have constant returns to scale even though individual firm production functions exhibit increasing returns[14]. However, in models such as Ethier (1982) where firms value diversity in intermediate inputs, there will be scale economies at the level of national industries if there are transport costs and other trade barriers which prevent costless trade in intermediate goods[15]. This hypothesis is investigated in the next section.

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[13] Note that the calculation of the TFP index (3) requires either an assumption of constant returns to scale or a priori knowledge of the degree of scale economies (see Caves, Christensen, and Diewert (1982), pg. 1394).

[14] In the Helpman-Krugman model, the scale of production of an individual firm depends on the elasticity of demand. In the tractable case of CES preferences and large numbers of firms, this elasticity is a constant, and changes in industry output are accommodated by changes in the number of firms rather than changes in the scale of existing firms. With more complex preferences which allow for changes in the elasticity of demand with changes in the number of varieties, there may be industry level economies of scale (see Brown (1991) and Lancaster (1984)).

[15] In Ethier's model, average costs are decreasing in the number of available varieties of differentiated intermediate goods. Under frictionless trade, costs are the same everywhere because firms in each country have access to the world total of varieties. With trade costs (whether tariffs or transport costs), firms in larger countries will have cheaper access to a wider range of intermediates, and hence lower costs, than firms in smaller countries.

4. Econometric Estimation of Technology Differences

This section describes a methodology for calculating cross-country productivity differences by econometric estimation of industry value added production functions. The purpose of the statistical model is to calculate measures of technological difference which explicitly allow for random variation in output, and to allow exploration of some hypotheses about the technology differences. The regression methodology also relies less heavily on economic theory than do index number comparisons of TFP. This is important since, as documented in Harrigan (1996), there is reason to believe that some of the assumptions which are necessary to construct TFP index numbers are violated in this data set. The cost of econometric analysis is that parameter estimation requires imposing a statistical model on the data, so the econometric results should be regarded as complements to rather than substitutes for the TFP index number calculations.

For a particular industry in country c in year t , write real value added y_{ct} as a function of the real capital stock k_{ct} and the level of employment l_{ct}:

$$y_{ct} = f_{ct}(k_{ct}, l_{ct}) \tag{7}$$

Hicks-neutral technical differences over time and across countries imply that this function can be written as

$$f_{ct}(k_{ct}, l_{ct}) = \beta_{ct} \cdot g(k_{ct}, l_{ct}) \tag{8}$$

Here, the factor of proportionality β_{ct} can be interpreted as an index of TFP. If the function $g(k_{ct}, l_{ct})$ is Cobb-Douglas, (7) can be written as

$$\ln y_{ct} = \alpha_{0ct} + \alpha_1 \ln k_{ct} + \alpha_2 \ln l_{ct} \tag{9}$$

or, subtracting $\ln l_{ct}$ from both sides,

$$\ln (y_{ct}/l_{ct}) = \alpha_{0ct} + \alpha_1 \ln(k_{ct}/l_{ct}) + \gamma \ln l_{ct} \tag{10}$$

where $\gamma = \alpha_1 + \alpha_2 - 1$. Equation (10) states that value added per worker depends on capital per worker and total employment. It is straightforward to show that the elasticity of scale of (10) is equal to $1 + \gamma$, so that γ is a convenient measure of the extent to which the industry production function differs from constant returns to scale.

The results reported in Table 1 make it clear that TFP varies across countries and over time, so any statistical model of cross-country variation in valued added per worker should allow for country effects and time trends. If there are country specific TFP effects which are common across industries, then pooling observations across industries is an efficient estimator. Using j to denote industries, a statistical model is

$$\ln y_{cjt}/l_{cjt} = \beta_{0c} + \beta_{1c} \cdot t + \alpha_j + \alpha_{1j} \ln(k_{cjt}/l_{cjt}) + \gamma_j \ln l_{cjt} + \epsilon_{cjt} \tag{11}$$

This model involves estimating industry specific intercept and slope terms (the α's and γ), and in addition supposing that each country's cross-industry average TFP is given by $\beta_{0c} + \beta_{1c} \cdot t$. An alternative way of modeling TFP differences is to suppose that there are industry specific time trends which are common across countries and that TFP differences are common for a particular country across industries. In this case, the statistical model is

$$\ln y_{cjt}/l_{cjt} = \beta_{0c} + \beta_{1j} \cdot t + \alpha_j + \alpha_{1j} \ln(k_{cjt}/l_{cjt}) + \gamma_j \ln l_{cjt} + \epsilon_{cjt} \tag{12}$$

Equation (11) is consistent with models of TFP growth with convergence in cross-industry TFP. TFP convergence (or divergence) is measured by differences in the cross-industry growth rate parameters β_{1c} across countries. Because of the short length of the panel in this paper and the short-term fluctuations in TFP that are evident in Table 1, it is very difficult to accurately estimate these country growth rate parameters, so I do not address convergence in this paper[16]. Equation (12) treats country TFP differences as constant over time, but allows for differential TFP growth rates across sectors. Equation (12) is consistent with TFP convergence or divergence at the level of total manufacturing to the extent that countries change their relative output mix over time.

Because of the short-run fixity of capital and because of labor hoarding, firms do not vary inputs in the short run proportionately with outputs, leading to strong cyclical movement in capacity utilization and measured TFP. A simple way to model this cyclicality is to suppose that capacity output is given by the production function, while actual output exceeds or falls short of capacity by an amount depending on the GDP gap, μ = (actual GDP)/(potential GDP):

$$y_{ct} = f_{ct}(k_{ct}, l_{ct}) \cdot \mu_{ct}^{\delta} \tag{13}$$

The parameter δ is the elasticity of capacity utilization with respect to the stage of the business cycle, and the specification has the feature that capacity utilization is 100% when $\mu = 1$. If $\delta > 1$, then industry capacity utilization is more cyclical than the economy, while $\delta < 1$ is the opposite case[17]. Potential GDP is estimated as the log-linear 20 year trend of actual GDP [18]. Preliminary data mining in cross-country

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[16] Convergence of industry level productivity is a central concern of Dollar and Wolff (1993) and Bernard and Jones (1996a and 1996b). These authors use overall GDP price levels to deflate sectoral outputs, so their results should be interpreted with caution for the reasons mentioned in the Introduction.

[17] A more sophisticated treatment of capacity utilization would define capacity as the minimum of the short run average cost curve, but the data required for such an adjustment is not available. See Morrison (1993), Chapter 3.

[18] The capacity utilization measure μ has a mean of one by construction, and a sample standard deviation of 2.5%. The standard deviation by country varies from a low of 1.3% (Japan) to a high of 4.6% (Norway).

regressions over time indicates that the null hypothesis of $\delta = 1$ can never be rejected at traditional significance levels for any industry, so I impose this simplifying restriction in what follows. This leads to the equation to be estimated:

$$\ln (y_{cjt}/l_{cjt}) - \ln \mu_{ct} = \beta_{0c} + \beta_{1j} \cdot t + \alpha_j + \alpha_{1j} \ln(k_{cjt}/l_{cjt}) + \gamma_j \ln l_{cjt} + \epsilon_{cjt} \tag{14}$$

Equation (14) includes time trends, so there is unlikely to be autocorrelation in $\{\epsilon_{cjt}\}$. However, the variance of ϵ_{cjt} is likely to differ by country and industry, and pre-testing rejects the null of constant variance[19]. Consistent estimates of σ^2_{cj} can be obtained as averages of the squared OLS residuals for each industry-country pair, but since there are at most ten observations for each industry-country pair such estimates will have a great deal of noise. Therefore, I model σ^2_{cj} as depending in a simple way on the partition into industries and countries:

$$\sigma^2_{cj} = \phi \sigma_c \sigma_j \tag{15}$$

Consistent estimates of σ_c and σ_j are the sample standard deviations of the OLS residuals from (14) for each industry c and country j; ϕ is a constant. Equation (15) along with the assumption of normality implies that $\epsilon_{cjt} \sim N(0, \phi\sigma_c\sigma_j)$. Consequently, the feasible generalized least squares (FGLS) estimator of (14) is weighted regression with weights given by $1/\hat{\sigma}_{cj}$.

A potentially very serious econometric problem in estimating (14) is correlation between the right hand side variables and the error term. This could occur for two reasons. The first is measurement error in capital and labor. The second is a simultaneity problem: if industry employment of factors increases due to a produc-

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[19] The null hypothesis of groupwise homoskedasticity is $\sigma^2_{cj} = \sigma^2$. A Lagrange Multiplier test of this null can be performed by regressing squared residuals from the OLS regression of (14) on a vector of K dummy variables d_{ij}, where $d_{ij} = 1$ for country i and industry j; the number of observations from this regression times the regression R^2 is a chi-squared statistic with K degrees of freedom. The value of this test statistic indicates rejection of the null at greater than the 0.01 level of significance.

tivity shock to the production function, then employment will be positively correlated with the error term. I have attempted to mitigate this simultaneity problem by controlling for the stage of the business cycle which is itself correlated with TFP. The appropriate solution to both the measurement error and simultaneity problems is to use an instrumental variables estimator, but I have not been able to find appropriate instruments. Therefore, the estimated parameters of (14) will not be consistent estimates of the structural parameters, so they should be interpreted with caution.

The Cobb-Douglas specification for value added is restrictive. In preliminary work, I estimated a translog specification, which differs from the specification in (14) by the inclusion of a quadratic term in the log of the capital-labor ratio, α_{3j} (ln $k_{cjt}\, l_{cjt}$). The translog is a flexible functional form, which is also a second order approximation to the constant-elasticity-of-substitution (CES) production function (see Kmenta, 1986, pg. 515). In this preliminary work, the correlation between the estimates $\hat{\alpha}_{1j}$ and $\hat{\alpha}_{3j}$ was virtually -1 for each industry j. A way of expressing this result is that the data can accurately estimate $\alpha_{1j} + \alpha_{3j}$, but that it is very uninformative about $\alpha_{1j} - \alpha_{3j}$. As a consequence of the data's inability to separately identify α_{3j}, all the results which follow set $\alpha_{3j} \equiv 0$ and are variants of the Cobb-Douglas specification.

5. Results

Table 5 reports estimates of three variants of equation (14) [20]. The estimator in each case is FGLS, as described above. Model 1 is the otherwise unrestricted equation. Model 2 imposes constant returns to scale ($\gamma_j = 0$, all j), and Model 3 excludes the country fixed effects ($\beta_{0c} = 0$, all i). The unrestricted model allows for

[20] Industry intercepts and constants are suppressed for readability.

two sources of industry productivity differences: differences in the scale of production within an industry and country-specific differences in productivity which are common across industries. The imposition of constant returns to scale in Model 2 means that any cross-country differences in productivity will be attributed to country-specific differences in productivity which are common across industries. Briefly, this is the "constant returns with different technology" hypothesis for explaining cross-country differences in industry productivity. In Model 3, by contrast, the exclusion of country effects means that any cross-country differences in industry productivity will be attributed to non-constant returns to scale, which can be labeled the "non-constant returns with identical technology" hypothesis. To aid interpretation, the country fixed effects reported are the exponential of the estimated coefficients; since the US is the excluded category, the exponentiated coefficients measure the proportionate TFP differential in machinery between a country and the US.

In model 1, the estimated coefficients on log capital per worker are reasonable except for an estimate of -0.63 for electrical machinery. A surprise from model 1 is that in no industry is there evidence of increasing returns to scale, and in five of the eight industries there are large and statistically significant estimated decreasing returns. In model 3, which excludes country fixed effects, this result is reversed: there are diseconomies of scale only in the electrical machinery sector, while there are large and statistically significant increasing returns in five of the eight industries.

This pattern of results may be partially explained by the fact that most of the variation in industry size is across countries. This suggests that larger countries may have disproportionately large industries due to moderate economies of scale, but that unrestricted estimation with this small data set can not sharply distinguish between country fixed effects and scale economies. This interpretation is strengthened by noting the change in the pattern of country fixed effects between models 1 and 2: when constant returns are imposed, the country fixed effects increase substantially relative to the US, the largest country in the sample. This negative correlation between estimated country effects and estimated scale economies was also noted by Maskus (1991).

Table 6 reports two types of test statistics which can shed further light on these issues. The first part of the table reports standard F-tests of the linear restrictions embodied in models 2 and 3; these restrictions are rejected at any conventional significance level. The second part of the table reports posterior odds ratios of the various combinations of hypotheses[21]. These odds ratios reflect the relative conditional probabilities of the different models, given equal prior probabilities and uninformative prior distributions. If we let ESS_1 denote the error sum of squares from the unrestricted Model 1, with ESS_2 and ESS_3 denoting the error sum of squares from the restricted Model's 2 and 3 respectively, then (for example) the posterior odds in favor of Model 2 over Model 1 is

$$B_{21} = \left(\frac{ESS_1}{ESS_2}\right)^{\frac{T}{2}} \cdot T^{\frac{p_2}{2}}$$

where p_2 is the number of restrictions embodied in Model 2 and T is the sample size. For comparison, the relationship between this posterior odds ratio and the usual F-statistic for testing the p_2 restrictions is

[21] see Leamer, 1978, pg. 112-114 for derivation and discussion of the formulas used here.

$$B_{21} = \left(F \cdot \frac{p_2}{T-k} + 1 \right)^{\frac{T}{2}} \cdot T^{\frac{p_2}{2}}$$

where F is the F-statistic and k is the number of parameters in the unrestricted Model 1. The main virtue of the posterior odds approach to hypothesis testing is that it permits the calculation of the relative probability of two hypotheses when both are rejected using classical tests (of course, such sensible comparisons are undefined in the classical framework). The relative likelihood of Model 2 compared to Model 3, B_{23}, is simply the ratio of B_{21} and B_{31} :

$$B_{23} = \left(\frac{ESS_3}{ESS_2} \right)^{\frac{T}{2}} \cdot T^{\frac{p_2 - p_3}{2}}$$

where p_3 is the number of restrictions embodied in Model 3. The posterior odds ratios indicate that the data support the unrestricted model over either restricted model, but that Model 2 fits the data substantially better than Model 3. Note also that only in Model 2 do all the estimated coefficients on the capital/labor ratio satisfy the theoretical restriction that they lie between zero and one. With a proper prior that embodied this theoretical restriction, the posterior odds ratios would be more favorable to Model 2 than is reported in Table 6.

The country fixed effects estimated in Models 1 and 2, which are estimates of overall TFP in machinery relative to the US level, are mainly reasonable in magnitude and thought-provoking. In Model 1, the US is the statistically significant TFP leader of every country through the 1980's. The laggard is Norway, with TFP of just

34% of the US level. Japanese TFP ranks second at about 82% of the US level, while Germany is third at 75% of the US level. In model 2, which imposes constant returns to scale, Japanese TFP is closer to the US level, at 93%, which is not statistically significantly different from 100%. German and Canadian TFP in Model 2 are about 90% of the US level, which is barely a statistically significant difference. The Australian results are not believable and can probably be attributed to the data anomaly noted above. Among the EC countries in the sample, Italy trails Germany and leads Britain and the Netherlands, each of which substantially trails the US. Finland, Norway and Sweden have TFP comparable to Britain and the Netherlands.

The industry TFP growth rates estimated in Model 1 range from a low of -1.7% per year for shipbuilding to a high of 12% per year for electrical machinery. Given the anomalous estimate for the effect of capital per worker on output in machinery, this large TFP growth rate is suspicious and should probably be discounted. Excluding electrical machinery, the fastest growth in TFP occurred in radio, TV, and communications equipment at 7.2% per year. Office and computing equipment and non-electrical machinery also had rapid TFP growth. This pattern of results does not differ much across the three specifications.

It is instructive to compare the results reported in Table 5 with the TFP index number comparisons reported in Tables 1, 2 and 3. Both the index numbers and the regression estimates rank the US as the leading country in TFP, with Japan very close to the US and Germany trailing somewhat. The largest difference is the relative ranking of Finland in Tables 3 and 5: the regression procedure reported in Table 5 does not weigh the good TFP performance of Finland's electrical machinery sector as heavily as the index number procedure of Table 3.

Another way to compare the Table 5 and TFP results is to compare the coefficient on the capital-labor ratio in Model 2 (where constant returns are imposed) with capital's share of total cost. If there is perfect competition in both input and output markets, the two numbers should be approximately the same. As Table 7 shows, the differences are small but statistically significant in most cases[22]. The regression results weight capital more heavily than capital's share in total cost, which is consistent with imperfect competition in input markets which cause the elasticities of outputs to differ from the factor cost shares.

6. Conclusion

This paper has constructed and analyzed a data set on real industry inputs and outputs for a group of industrialized countries during the 1980s. The results of the paper confirm the view that there are large and persistent differences in TFP across the industrialized countries. This inference was suggested by the TFP comparisons of Table 1, and is supported by the econometric data analysis of the previous section.

The econometric results suggest that industry-level economies of scale are probably not large, and almost certainly can not account for the large size of cross-country TFP differences. This suggests several alternative hypotheses. The first is that there are technological differences across the developed countries, a view which conflicts with the traditional presumption of international trade economists that production sets are the same everywhere. This hypothesis is supported by the data analysis here, in the sense that the hypothesis fits the data better than the increasing returns hypothesis, and also produces the most plausible parameter

[22] The differences are jointly statistically significant at greater than the .1% level of confidence.

values of the three statistical models that are estimated. A variant on this hypothesis which does not require supposing differential access to technical knowledge is that there are differences in the legal, social, and political environments across countries which have major effects on TFP. Unfortunately, this is a hard hypothesis to investigate empirically.

A third alternative is that there is systematic measurement error in the components of the TFP index. If this view is correct, better measurement will narrow observed TFP differences. While this can not be ruled out, it should be noted that this paper has used disaggregated price and labor data and the resulting estimated TFP differences, while often somewhat different from previous studies, are not smaller.

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Table 1 - Total Factor Productivity, relative to US Level in 1987

Country	Year	Non-Electrical Machinery	Office & Computing Equipment	Electrical Machinery, exc. comm.	Radio, TV, & Communications eq.	Motor Vehicles	Aircraft
Australia	80			223	108	88	
	81			235	118	87	
	82			245	136	94	
	83			135	84	52	
	84			134	97	58	
	85			134	97	58	
Britain	80	40	44	52	33	25	
	81	38	43	56	38	25	
	82	41	49	70	46	28	
	83	43	51	77	52	31	
	84	49	55	95	65	36	
	85	58	62	116	76	43	39
	86	61	59	113	72	44	46
	87	65	63	108	68	41	42
	88	65	69	113	72	44	45
Canada	80	122	60	117	89	67	87
	81	107	54	122	85	61	95
	82	84	51	110	82	57	77
	83	75	42	105	71	79	41
	84	85	45	113	77	88	64
	85	89	43	125	74	87	65
	86	99	39	130	75	75	56
	87	100	43	137	88	64	65
	88	108	53	161	94	73	60
Finland	80	49	90	81	31	32	
	81	53	99	89	38	31	
	82	56	93	99	56	31	
	83	56	79	108	67	34	
	84	67	89	121	69	38	
	85	85	75	152	91	45	
	86	83	84	164	96	47	
	87	109	109	178	121	50	
	88	114	104	218	105	54	
	89	119	57	254	132	58	46

Table 1, continued

Country	Year	Non-Electrical Machinery	Office & Computing Equipment	Electrical Machinery, exc. comm.	Radio, TV, & Communications eq.	Motor Vehicles	Aircraft
Germany	80	62	51	63	61	63	62
	81	60	51	62	69	66	68
	82	57	56	67	79	71	67
	83	58	59	75	88	75	64
	84	64	62	89	97	78	70
	85	78	67	105	112	91	74
	86	74	64	103	102	78	69
	87	78	61	101	102	75	70
	88	78	66	104	110	73	72
	89	80	60	95	110	72	84
Italy	85	76	48	152	77	53	72
	86	76	44	148	71	49	63
	87	84	43	149	73	54	
	88					199	
Japan	80	77	61	103	63	105	
	81	77	56	103	67	94	
	82	73	57	109	65	83	
	83	67	58	107	64	79	
	84	64	78	112	70	76	
	85	80	57	118	66	80	
	86	79	54	120	63	74	
	87	84	53	131	69	83	
	88	94	59	159	86	101	
	89	98	62	180	96	115	
Netherlands	80	51	50			138	
	81	53	42			92	
	82	55	44			51	
	83	53	54			53	
	84	59	72			58	
	85	76	44			59	
	86	78	59			61	
	87	89	45			56	
	88	84	49			82	

Table 1, continued

Country	Year	Non-Electrical Machinery	Office & Computing Equipment	Electrical Machinery, exc. comm.	Radio, TV, & Communications eq.	Motor Vehicles	Aircraft
Norway	80	50	27	69	33	32	38
	81	51	32	86	37	31	41
	82	51	37	85	41	31	36
	83	51	37	92	49	31	32
	84	56	40	98	56	33	32
	85	70	40	117	61	36	36
	86	77	44	140	69	36	24
	87	87	32	155	78	36	41
	88	85	30	159	81	37	39
	89	89	26	165	77	38	39
USA	80	103	99	54	119	73	
	81	101	97	59	111	71	
	82	91	91	32	111	68	92
	83	88	81	29	108	91	95
	84	91	88	26	115	102	104
	85	97	79	43	108	105	105
	86	102	81	43	106	100	99
	87	100	100	100	100	100	100
	88	108	110	114	116	117	103
	89	112	114	115	122	125	107

Table 2 - Summary of Table 1, Average TFP relative to US Average TFP, detrended

	Non-Electrical Machinery	Office & Computer Equipmnt	Electrical Machinery	Radio, TV, & Comm.	Motor Vehicles	Shipbuilding	Aircraft	Other Trans. Equip.
Australia			262	86	61	67		
Britain	52	58	166	52	37	38	42	
Canada	99	51	241	76	78	81	66	96
Finland	76	93	256	66	44	51	46	
Germany	69	64	158	82	79	78	69	
Italy	73	48	245	60	73	52	67	83
Japan	79	63	229	63	94	100		
Netherlnd	67	54			75	119		84
Norway	65	36	209	50	36	45	35	
Sweden						50		

Notes to Table 2: The numbers in this table are regression-based summaries of the TFP data in Table 1. Each entry is 100 times the exponential of the country fixed effect D_c in the following regression for sector j:

$$\ln TFP_{cjt} = D_{cj} + \delta_j \cdot t + \epsilon_{cjt}$$

where $\ln TFP_{cjt}$ is the log of industry j TFP in country c in year t relative to the sample mean TFP of industry j. The United States is the excluded fixed effect, so the entries in the table are percentage differences from the United States.

Table 3 - Overall TFP in Machinery & Equipment

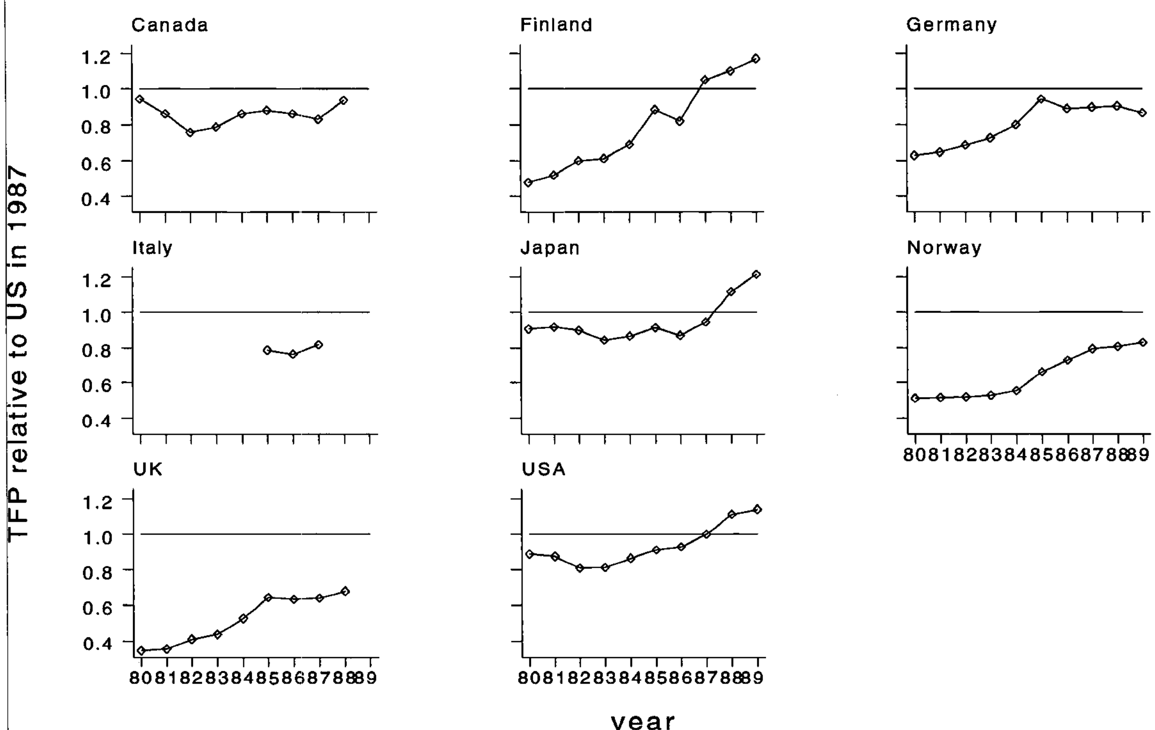
	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Panel A: TFP is expressed relative to a base of United States in 1987 = 100										
Britain	35	36	41	44	53	64	63	64	68	
Canada	94	86	76	79	86	88	86	83	93	
Finland	48	52	60	61	69	89	82	105	110	117
Germany	63	65	69	73	80	94	89	90	90	86
Italy						79	76	82		
Japan	91	92	90	84	87	91	87	95	112	121
Norway	51	52	52	53	56	66	73	79	81	83
United States	89	88	81	82	87	91	93	100	111	114
Panel B: TFP is expressed relative to a base of United States in each year = 100										
Britain	39	41	51	54	61	70	68	64	61	
Canada	106	98	93	96	99	97	93	83	84	
Finland	54	59	74	75	80	97	88	105	99	103
Germany	71	74	85	89	92	104	95	90	81	76
Italy						86	82	82		
Japan	102	105	111	103	100	100	94	95	100	106
Norway	58	59	64	64	64	73	78	79	72	72
United States	100	100	100	100	100	100	100	100	100	100

Notes to Table 3: The TFP comparisons in this table are index numbers using the industry level data presented in Table 1. Data for two of the eight industries, Aircraft and Other Transport Equipment, are excluded. For the index number formula used in this table, see equation (6) in the text. Panel A of this table is graphed in Figure 1, and Panel B is graphed in Figure 3.

Table 4 - Overall TFP in Machinery & Equipment, adjusted for Business Cycle

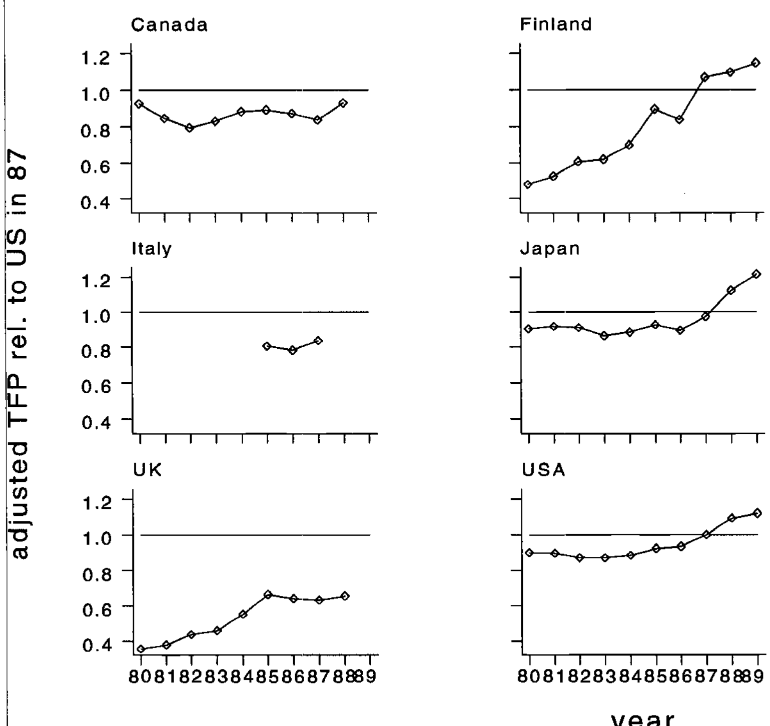
Panel A: TFP is expressed relative to a base of United States in 1987 = 100										
	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Britain	36	38	44	46	55	67	64	64	66	
Canada	93	85	80	83	88	89	87	84	93	
Finland	48	52	61	62	70	90	84	107	110	115
Germany	61	65	71	75	82	97	91	93	92	87
Italy						81	79	84		
Japan	91	92	91	86	89	93	90	97	113	122
Norway	49	51	53	53	55	64	70	78	83	90
United States	90	90	87	87	89	92	94	100	109	112
Panel B: TFP is expressed relative to a base of United States in each year = 100										
Britain	40	42	50	53	62	72	68	64	60	
Canada	103	94	91	96	100	97	93	84	85	
Finland	53	59	70	71	79	97	90	107	100	102
Germany	68	72	81	86	93	105	97	93	84	77
Italy						87	84	84		
Japan	100	103	105	99	100	100	96	97	103	108
Norway	54	57	60	61	62	70	75	78	76	80
United States	100	100	100	100	100	100	100	100	100	100

Notes to Table 4: This table differs from Table 3 by multiplying each country's output by the ratio of trend to actual GDP. This is a way of smoothing out TFP variability which is caused by business cycle variation in capacity utilization. See also the notes to Table 3. Panel A of this table is graphed in Figure 2, and Panel B is graphed in Figure 4.



TFP Relative to US in 1987

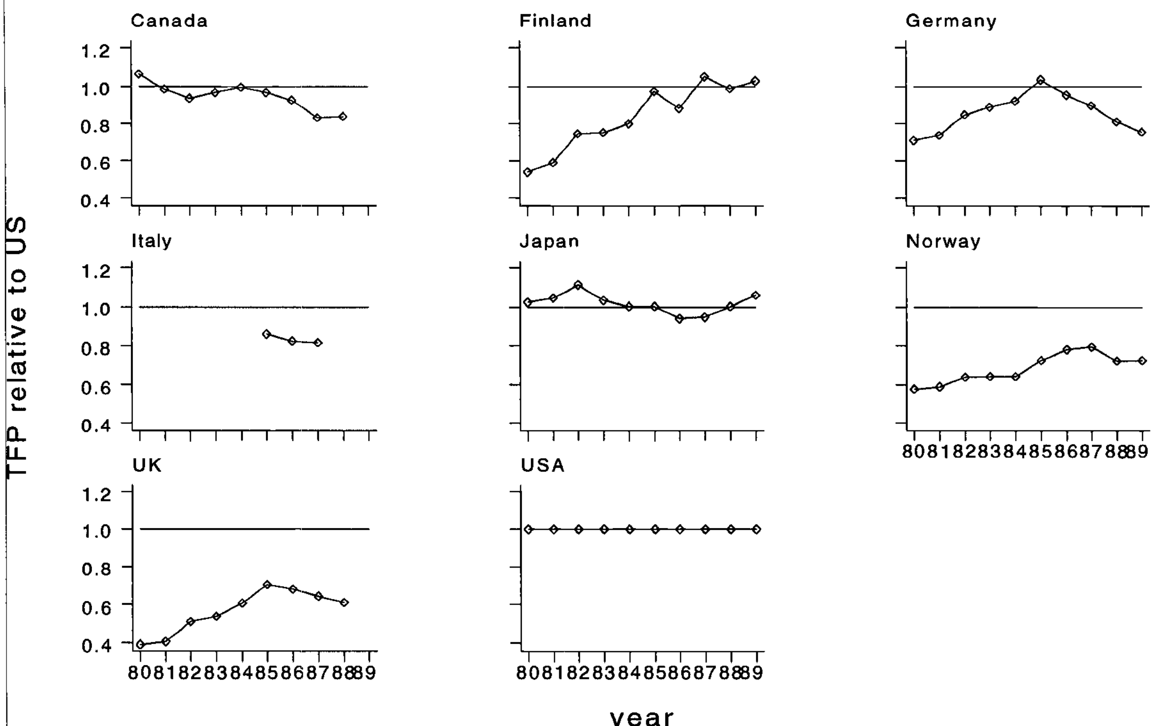
Figure 1



TFP adjusted for business cycle, Relative to US in 1987

Figure 2

Notes to Figures: Figure 1 presents the data in Panel A of Table 3. Figure 2 presents the data in Panel A of Table 4.



TFP, Relative to US

Figure 3

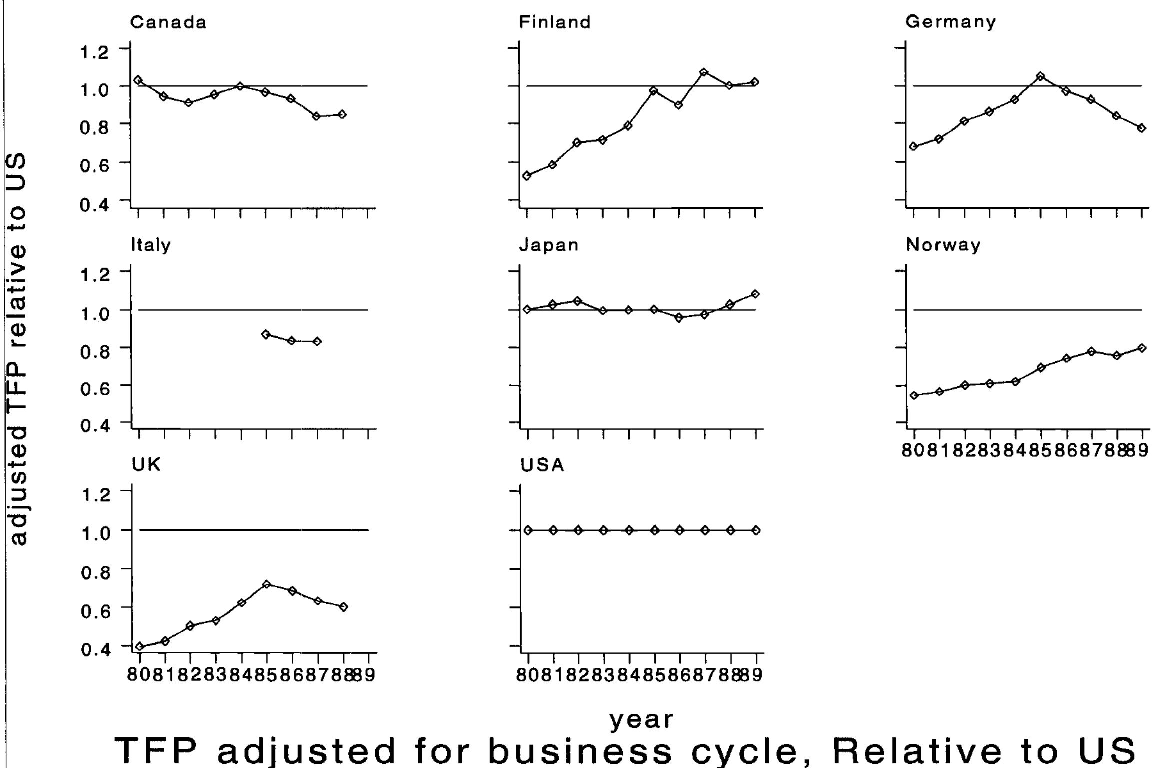


Figure 4

Notes to Figures: Figure 3 presents the data in Panel B of Table 3. Figure 4 presents the data in Panel B of Table 4.

Table 5 - Estimates of Equation (14)						
dependent variable: Log Value Added per Worker, adjusted for capacity utilization number of observations = 566						
	Model 1 R^2 = 0.80		Model 2 R^2 = 0.71		Model 3 R^2 = 0.64	
	coef.	t	coef.	t	coef.	t
Log Capital per Worker						
Non-electrical Machinery	0.232	2.84	0.441	5.04	0.390	4.09
Office & Computing Equipment	0.209	4.23	0.256	4.62	0.289	4.88
Electrical machinery, except comm.	-0.631	-6.23	0.336	3.48	-0.216	-1.89
Radio, TV, & comm. equipment	0.222	2.80	0.388	4.78	0.580	6.12
Shipbuilding & Repairing	0.422	4.15	0.288	3.05	0.522	4.26
Motor Vehicles	0.548	6.58	0.714	7.59	0.938	9.67
Aircraft	0.189	1.97	0.363	3.20	0.567	4.72
Other transport equipment	0.342	3.07	0.291	2.85	0.320	2.51
Log Industry Employment						
Non-electrical Machinery	-0.157	-5.37			0.031	1.45
Office & Computing Equipment	-0.066	-2.66			0.087	4.60
Electrical machinery, except comm.	-0.373	-12.3			-0.168	-6.58
Radio, TV, & comm. equipment	-0.100	-4.14			0.058	3.06
Shipbuilding & Repairing	-0.051	-1.21			0.133	3.54
Motor Vehicles	-0.018	-0.87			0.096	6.35
Aircraft	-0.008	-0.34			0.160	7.53
Other transport equipment	-0.276	-2.59			0.055	0.51

(Table continues on next page)

Table 5 - Estimates of Equation (14)						
dependent variable: Log Value Added per Worker, adjusted for capacity utilization number of observations = 566						
	Model 1 R^2 = 0.80		Model 2 R^2 = 0.71		Model 3 R^2 = 0.64	
	coef.	t	coef.	t	coef.	t
Industry Trends						
Non-electrical Machinery	0.051	5.70	0.045	4.35	0.047	4.00
Office & Computing Equipment	0.030	2.76	0.025	1.95	0.019	1.40
Electrical machinery, except comm.	0.121	10.88	0.067	5.01	0.094	6.75
Radio, TV, & comm. equipment	0.072	6.42	0.058	4.68	0.034	2.31
Shipbuilding & Repairing	-0.017	-1.82	-0.008	-0.80	-0.011	-0.92
Motor Vehicles	0.018	1.95	0.015	1.41	-0.002	-0.17
Aircraft	0.000	-0.01	-0.010	-0.60	-0.041	-2.39
Other transport equipment	0.001	0.04	0.005	0.22	0.005	0.18
Country Fixed Effects (exponentiated to give proportion of US=1)						
Australia	0.754	-2.75	1.147	1.91		
Britain	0.470	-13.35	0.618	-8.74		
Canada	0.639	-5.91	0.907	-2.06		
Finland	0.463	-7.61	0.749	-5.40		
Germany	0.748	-5.97	0.896	-2.24		
Italy	0.680	-5.47	0.741	-4.70		
Japan	0.816	-3.97	0.932	-1.23		
Netherlands	0.562	-6.07	0.822	-3.33		
Norway	0.343	-10.30	0.548	-12.50		
Sweden	0.415	-7.49	0.578	-5.97		

Table 6 - Test Statistics

Note: All test statistics are calculated using the FGLS estimates of equation (14). The different hypotheses are

Model 1: Unrestricted; Variable Returns to Scale/Different Technology

Model 2: $\gamma_j = 0$, all j; Constant Returns to Scale/Different Technology

Model 3: $\beta_{0i} = 0$, all i; Variable Returns to Scale/Identical Technology

F-tests

Null: Model 2

$F(8,524) = 31.50$ 1% Critical Value = 2.545

Null: Model 3

$F(10,524) = 41.33$ 1% Critical Value = 2.355

Posterior Odds Ratios

Pr(Model 2 | data)/Pr(Model 1 | data) = 5.29×10^{-60}

Pr(Model 3 | data)/Pr(Model 1 | data) = 5.77×10^{-86}

Pr(Model 2 | data)/Pr(Model 3 | data) = 9.16×10^{25}

Table 7 - Comparison of Regression & TFP Weights on Capital

	(1)	(2)	(3)
Non-electrical Machinery	0.441	0.201	0.006
Office & Computing Equipment	0.256	0.426	0.002
Electrical machinery, except comm.	0.336	0.154	0.060
Radio, TV, & comm. equipment	0.388	0.327	0.448
Shipbuilding & Repairing	0.288	0.055	0.014
Motor Vehicles	0.714	0.254	0.000
Aircraft	0.363	0.170	0.089
Other transport equipment	0.291	0.237	0.595
Unweighted average	0.385	0.228	

Notes to Table 7: Column (1) is the coefficient on the capital-labor ratio in Model 2, reproduced from Table 5. Column (2) is the average of capital's weight in the TFP calculations of Table 1. Column (3) is the marginal significance level of the difference between columns (1) and (2).