

Development-Related Biases in Factor Productivities and the HOV Model of Trade

Keith E Maskus and Shuichiro Nishioka*

University of Colorado at Boulder

February 2007

Abstract

Past empirical failures of the basic Heckscher-Ohlin-Vanek (HOV) model related to the inability of data to meet its restrictive assumptions, particularly identical international technologies and factor price equalization. Trefler (1993) tried to resuscitate HOV by introducing a simple Hicks-neutral (HN) factor-productivity adjustment, an approach that was heavily criticized. In this paper, we re-examine the productivity question by estimating factor-specific productivities from the individual technology data of multiple countries. Using a dataset of 15 OECD countries, we find evidence of factor-augmenting technological differences. Further, we find that the ratios of factor productivities are strongly correlated with corresponding factor endowments. This systematic bias implies that the ability of HOV to explain North-South factor trade depends both on relative factor abundance and productivity gaps. We thus extend Debaere's (2003) conclusion that North-South trade is determined by HN-adjusted endowment differences.

Keywords: Heckscher-Ohlin-Vanek; Factor Trade, Productivity

JEL classifications: F11 (Neoclassical Model of Trade)

* Keith E Maskus: Department of Economics, University of Colorado at Boulder, 256 UCB Boulder 80309-0256
Tel: +1(303)492-7588 E-mail: keith.maskus@colorado.edu Shuichiro Nishioka: Department of Economics,
University of Colorado at Boulder, 256 UCB Boulder 80309-0256 Tel: +1(303)579-6542 E-mail:
snishioka@colorado.edu We particularly thank Wolfgang Keller and James R. Markusen. All errors remain our
responsibility.

1. Introduction

Early tests of the Heckscher-Ohlin-Vanek (HOV) model of international factor trade demonstrated that it failed to predict trade better than a coin toss (Maskus, 1985; Bowen, Leamer and Sveikauskas, 1987). As noted by Maskus (1985), the assumptions of the strict HOV model are too unrealistic to expect them to generate actual data.¹ Later tests relaxed many of these assumptions to generate extended HOV models that were more consistent with data (Trefler, 1995; Davis and Weinstein, 2001; Davis, et al, 1997; Hakura, 2001). Much of this analysis has focused on the unrealistic assumptions of internationally identical technologies and factor price equalization (FPE).

Trefler (1993) made a first important step to integrate international differences in factor-prices into the HOV model. He introduced a simple Hicks-neutral (HN) productivity modification at the individual factor level to measure endowments in productivity-equivalent units. For example, if the labor supplies of the United States and Brazil were the same, but U.S. workers were twice as productive, the former nation would have twice as much labor at the productivity-equivalent level.² At the same time, the wage of U.S. workers would be twice that of Brazilian workers and ratios of factor prices could be used to infer relative productivities. This modification is consistent with the HOV model after adjusting for international differences in factor productivity.

Davis and Weinstein (2001) argued that Trefler's productivity modification is incomplete because it fails to introduce general differences in technology. With step-by-step relaxations of

¹ The strict version assumes: (1) identical constant returns to scale (CRS) technology and factor price equalization; , (2) perfectly competitive markets in goods and factors; (3) identical and homothetic preferences; (4) factor endowment differences; and (5) free trade in goods but not factors.

² This was Leontief's (1953) conjecture to explain his celebrated paradox.

the standard HOV assumptions, they found substantial improvements in prediction power when national technologies are modified according to factor abundance measures.

Though both studies focused on modifying FPE, the conceptual distinction between their empirical approaches is important. Is it differences in productivity of factors or underlying technology that is responsible for factor price disparity? If it is because of factor-productivity differences, the HOV model is fundamentally acceptable, for its failures would come from the inability to measure factors in productivity-equivalent units. However, if the failures occur because of general technology differences, both the standard HOV model and FPE break down.

Several papers analyzing factor abundance have relied on Trefler's method to justify the introduction of productivity adjustments (Trefler, 1995; Antweiler and Trefler, 2002; Debaere, 2003; Fitzgerald and Hallak, 2004). However, the validity of his results has been questioned. Gabaix (1997), for example, showed that Trefler's adjustment to labor productivity (capital productivity) merely reflects differences in GDP/labor (or GDP/capital) due to his method of deriving productivities. There is surely a strong correlation between GDP per unit of factor and factor prices that may not be solely the result of differences in productivity. Thus, Trefler's claim of strong support for the standard HOV model is questionable unless factor productivities are estimated appropriately.

In this paper we introduce a different approach to estimate factor-specific productivities based solely on a constant returns to scale (CRS) production function.³ This methodology permits extending Trefler's approach to HOV testing without facing the argument made by Gabaix. Using a newly constructed dataset covering 15 OECD countries, we find evidence for the notion of basic factor-augmenting technology differences. Moreover, incorporating

³ Our approach builds on that of Maskus and Webster (1999). Those authors were concerned with ranking endowments across the United States and the United Kingdom, assuming the HOV model to be valid, rather than testing the trade model itself.

estimated factor productivities raises the fit of the standard HOV signs test from 56.7 percent to 76.7 percent and increases the variance ratio from 0.002 to 0.233.

More fundamentally, we also find that the estimated productivities are strongly correlated with aggregate factor abundance in a relative sense. For example, workers in Japan, which is capital abundant, are productive (relative to Japanese capital) because they have access to machines and computers that make workers efficient. This systematic correlation between labor-productivity and capital-abundance, which is consistent with general principles of the factor-proportions model of trade without FPE, was previously discussed by Dollar, Wolff, and Baumol (1988). Moreover, the idea of factor-specific productivity is strongly related to the literature on skill-biased technological change (Krusell, et al, 2000; Caselli and Coleman II, 2006). Because the rapid growth of physical capital interacts differently with different types of labor, capital productivity and labor productivity evolve differently with the stages of economic development. In particular, capital-skill complementarity could play a key role because the efficient operation of highly productive capital in developed countries requires skilled labor.⁴ Its importance here is that the empirical success of Trefler's basic model can be attributable to systematic productivity differences across factors that cannot be obtained from the Hicks-neutral form. Thus, similar to Davis and Weinstein (2001) who adjusted national technologies according to factor abundance, our results also indicate the important link between technology, productivity, and factor abundance.⁵ However, rather than general technology differences we consider only factor-

⁴ Krusell et al (2000) defined capital-skill complementarity as the situation where the elasticity of substitution between capital and unskilled labor is higher than that between capital and skilled labor. In this paper, we will show that skilled-labor productivity and capital productivity co-move with economic development but these productivities move differently from unskilled-labor productivity.

⁵ Davis and Weinstein relied on the Dornbusch, Fischer, and Samuelson (1980) model and Helpman's (1999) multiple-cone model of specialization to motivate this correlation.

augmenting, industry-neutral productivity variations. This more restricted specification achieves considerable success for HOV.

Our finding points out a potential danger in applying strict HOV-type models in a relative (i.e., bilateral) sense because factor productivity interacts systematically with factor abundance. For example, Debaere (2003) demonstrated that the HOV equation holds better for South-North country pairs than for North-North country pairs. But this finding raises the question of whether South-North factor-productivity gaps or South-North factor-abundance differences drive support for the factor contents of trade. In fact, we show that the reason Debaere found strong evidence only for South-North country pairs of particular factor combinations is likely systematic South-North differences in factor productivity. Because the abundant factor (unskilled labor) has limited access to capital and skilled labor in the South, its productivities are systematically lower than those of capital and skilled labor. However, Northern data do not entail this feature. This productivity gap contributes to the support found for Debaere's theoretical prediction involving only relative factor abundance for South-North country pairs. Therefore, it is hard to conclude that the success of the relative factor-abundance model is purely derived from South-North differences in adjusted factor endowments. Rather, both differences in factor productivities and factor endowments are responsible, with the balance of each element being unclear.

We organize the paper as follows. In Section 2 we revisit Trefler's (1993) model and the criticism in Gabaix (1997). In Section 3 we set out our empirical results from the estimation of factor productivities and relate them to Trefler's approach. In addition, we study the characteristics of estimated productivities, particularly the correlation between productivity and factor abundance. In section 4 we examine the potential biases from ignoring factor

productivities in the context of Debaere's (2003) relative factor-abundance model. Concluding remarks are offered in the final section.

2. The HOV Model and Factor-Augmenting Productivity

We begin by deriving the basic HOV prediction in a world with F factors, C countries, and N products (sectors). Assume that all countries have identical constant returns to scale production technology; markets for goods and factors are perfectly competitive; there are no barriers to trade and zero transportation cost; factors move freely within a country but do not move across countries; and the distribution of factors is consistent with integrated equilibrium so that factor prices are equalized across countries.

For each country c the net-export vector can be obtained as the difference between net production and the final consumption:

$$T_c = (I - B_c)Q_c - C_c \quad (1)$$

where T_c is an $N \times 1$ vector of net exports, Q_c is an $N \times 1$ vector of gross output, and C_c is an $N \times 1$ vector of final consumption. B_c is an $N \times N$ input-output (indirect) matrix for the unit intermediate requirements so that $(I - B_c)Q_c$ equals the net output vector Y_c .

Let A_c be the $F \times N$ direct technology matrix and its elements (a_{cif}) represent the amount of a factor needed to produce one unit of gross output in sector i . Pre-multiplying equation (1) by direct and indirect technology matrix $A_c(I - B_c)^{-1}$ and applying the factor-exhaustion assumption $A_c Q_c = V_c$ where V_c is an $F \times 1$ vector of factor endowments, we have that a country's factor contents of trade is the difference between factors absorbed in production ($A_c Q_c = V_c$) and factors absorbed in final consumption ($A_c(I - B_c)^{-1} C_c$):

$$A_c(I - B_c)^{-1} T_c = V_c - A_c(I - B_c)^{-1} C_c \quad (2)$$

Assuming identical and homothetic preferences, along with identical prices of goods and services, the final consumption vector is proportional to the world net output vector (Y_w):

$$C_c = s_c Y_w \quad (3)$$

where s_c is a scalar representing the share of country c in world expenditure. Because the production technology is identical worldwide and there is FPE, the technologies of the United States may be used to derive the following standard HOV equation:

$$F_c = V_c - s_c V_w \quad (4)$$

where $F_c = A_{US}(I - B_{US})^{-1} T_c$ is measured factor contents of trade with U.S. technologies and $V_c - s_c V_w$ is predicted factor contents of trade. Thus, the HOV model tells us that measured factor contents of trade for any country can be predicted by that country's factor endowments, the world factor endowments, and final consumption shares.

To integrate factor productivity into the HOV model, Treﬂer (1993) introduced coefficients (π_{cf}) with the interpretation that if V_{cf} is the factor endowment of country c then $V_{cf}^* = \pi_{cf} V_{cf}$ is the corresponding factor endowment measured in productivity-equivalent units. Let w_{cf} be the price per unit of V_{cf} and let w_{cf}^* be the price per unit of V_{cf}^* . Since one unit of V_{cf} provides π_{cf} productivity-equivalent units of service, $1/\pi_{cf}$ units of V_{cf} provide one productivity-equivalent unit service priced at $w_{cf}^* = w_{cf} / \pi_{cf}$. Assuming identical technologies at the productivity-equivalent level and normalizing factor productivities of the United States to unity, the system of equations (5) and (6) follows:

$$F_{cf} = \pi_{cf} V_{cf} - s_c \sum_{g=1}^G \pi_{gf} V_{gf} \quad (5)$$

$$w_{cf} / \pi_{cf} = w_{USf} / \pi_{USf} \Leftrightarrow w_{cf} / w_{USf} = \pi_{cf} / \pi_{USf} \quad (6)$$

where equations (5) capture the elements of $F_c = A_{US}(I - B_{US})^{-1}T_c$, $\pi_{USf} = 1$, and g is the index of countries in the dataset. This framework is the efficiency-unit HOV model in Treﬂer (1993) in which the standard HOV model is adjusted by factor productivities.

2.A. Treﬂer's Derivation of Factor-Productivity

Treﬂer built the extended HOV model with the system of equations (5) and (6), using a dataset for 33 countries. Equation (5) is the HOV model with productivity-equivalent factors and equation (6) indicates that FPE holds when international factor productivities are adjusted.

To estimate factor productivities (π_{cf}), Treﬂer derived equation (7) from equation (5):

$$F_f = X_f \Pi_f \quad \text{where} \quad F_f = \begin{bmatrix} F_{1f} \\ F_{2f} \\ \vdots \\ F_{cf} \end{bmatrix}, X_f = \begin{bmatrix} (1-s_1)V_{1f} & -s_1V_{2f} & \cdots & -s_1V_{cf} \\ -s_2V_{1f} & (1-s_2)V_{2f} & \cdots & -s_2V_{cf} \\ \vdots & \vdots & \ddots & \vdots \\ -s_cV_{1f} & -s_cV_{2f} & \cdots & (1-s_c)V_{cf} \end{bmatrix}, \Pi_f = \begin{bmatrix} \pi_{1f} \\ \pi_{2f} \\ \vdots \\ \pi_{cf} \end{bmatrix} \quad (7)$$

Normalizing the productivities in terms of the United States, the π_{cf} parameters may be estimated by ordinary least squares (OLS). However, once these estimated factor productivities are introduced into equation (5) it is inappropriate to apply standard testing procedures of the HOV model because fitted values for predicted factor contents of trade are identical to measured factor contents of trade. That is, all the HOV test statistics automatically would indicate a perfect fit.⁶

To deal with this issue Treﬂer set out two alternative methods to demonstrate the validity of his estimated factor productivities. One was to check the signs of the productivity parameters, with all expected to be positive. The other was to study the correlation between relative price (w_{cf}/w_{USf}) and relative productivity (π_{cf}/π_{USf}) in equation (6) for each factor, with the correlation

⁶ Because OLS forces the productivity parameters to equalize measured factor contents of trade (FCT) and fitted (predicted) factor contents of trade (FCT): $F_f \equiv \hat{F}_f = X_f \hat{\Pi}_f$, the measured FCT (F_f) and the predicted FCT ($X_f \hat{\Pi}_f$) are nearly identical.

expected to be unity. Treﬂer noted that the productivities estimated from equation (7) were positive and that equation (6) performed well, with the correlation for labor being 0.90 and that for physical capital being 0.68.

While the approach generated a number of comments, Gabaix (1997) in particular criticized this methodology for deriving the estimation method (equation (7)) testing factor productivities. His reasoning came from the “missing trade” phenomenon analyzed in Treﬂer (1995). Missing trade is the ﬁnding that measured factor contents of trade are generally very small relative to predicted factor contents of trade. Thus, if the vector of measured factor contents of trade were virtually zero in equation (5), we would have:

$$0 = \pi_{cf}V_{cf} - s_cV_{wf}^* \Leftrightarrow \pi_{cf} = s_c \frac{V_{wf}^*}{V_{cf}} = \frac{Y_c}{Y_w} \frac{V_{wf}^*}{V_{cf}} = \frac{Y_c}{V_{cf}} R \quad (8)$$

where world aggregates ($V_{wf}^* = \sum_g \pi_{gf} V_{gf}$ and $R = V_{wf}^*/Y_w$) are essentially independent of the data from country c . In the case of labor, for example, the estimated productivity of labor would equal GDP per worker. Therefore, it is not surprising that Treﬂer’s estimated productivities were positive and correlated strongly with factor prices. In this context, Treﬂer’s approach offered no independent validation for the empirical success of his productivity modiﬁcation of HOV.

Although Gabaix’s criticism does invalidate Treﬂer’s methodology and statistical evidence, it does not necessarily mean the rejection of Treﬂer’s model *per se*. Rather, if it were possible to estimate factor-productivity parameters independently of the equation system, incorporating them would not make HOV a truism and standard testing procedures would be valid. To this end, we develop unit total factor requirements (technologies A_c and B_c) for each country and estimate factor productivities for each country across sectors. These estimated parameters are then incorporated to test equations (5) and (6). This procedure escapes the problems Gabaix (1997) pointed out.

2.B. The Modified Approach

Within Trefler's framework, countries share identical production technologies at the productivity-equivalent level, making adjusted unit factor requirements identical across countries for each factor: $a'_{USif} = a'^*_{cif}$ for country c and factor f where a'^*_{cif} is $\pi_{cf} a'_{cif}$. If firms minimize unit cost functions with CRS technology, the quantity of factor f required in sector i divided by corresponding output is the unit factor requirement: $a'_{USif} = V_{USif}/Q_{USif}$ for the United States and $V^*_{cif}/Q_{cif} = \pi_{cf} V_{cif}/Q_{cif} = \pi_{cf} a'_{cif} = a'^*_{cif}$ for country c .

We estimate the productivity parameters (π_{cf}) by regressing the unit factor requirements of the United States against those of individual countries. This approach was proposed by Maskus and Webster (1999) in developing their "factor-augmenting, industry-neutral (FAIN)" specifications. Thus, consider the simple regressions:

$$a'_{USif} = \pi_{cf} a'_{cif} + \varepsilon_{cif} \quad (9)$$

where a'_{cif} embraces direct and indirect technologies.⁷ These equations are estimated using data that vary across 22 sectors for each country. The estimation approach is seemingly unrelated regressions (SUR). We assume that these factor requirements are generated by a process obeying the FAIN assumption, with measurement errors randomly distributed around zero and embodied in the residual terms.⁸

Using the estimated factor-productivities from equation (9), we test both equations (5) and (6). This implicitly assumes that no other sources of international differences in unit factor requirements (technologies) exist after international factor productivities are adjusted. Because the factor-productivities are estimated solely from unit factor requirements, it is possible to

⁷ Total technology (direct and indirect): $A'_c = A_c(I - B_c)^{-1}$.

⁸ Maskus and Webster (1999) discuss potential types of measurement error.

examine equations (5) and (6) separately and apply standard testing procedures of the HOV model to equation (5). In addition, we can separately assess equation (6) in terms of the correlations between price and productivity for each factor.

In testing HOV we consider both the aggregate specification in (5) and the pair-wise HOV model (Staiger, Deardorff, and Stern, 1987; Hakura, 2001). The primary advantage of the pair-wise HOV model is that the testing equation does not include world aggregates. Because our dataset consists of 15 OECD countries, there is some question about data sums representing world aggregates. To derive the pair-wise model, apply equation (4) to two arbitrarily chosen countries. For example, take the ratio of the United States ($c=1$) and Japan ($c=2$) and cancel the net world output (Y_w) in equation (3) ($C_1=s_1/s_2C_2=\alpha C_2$). Then, with appropriate subtraction, the pair-wise HOV model follows:

$$F_1 - \alpha F_2 = V_1 - \alpha V_2 \quad (10)$$

where $F_1 - \alpha F_2$ is the measured relative factor contents of trade with country 2's technology ($F_1 = A_1(I-B_1)^{-1}T_1$ and $F_2 = A_2(I-B_2)^{-1}T_2$) and $V_1 - \alpha V_2$ is the predicted relative factor content of trade.⁹

We next apply our estimated factor productivities to the pair-wise HOV model. In this model, technology differs more generally than in equation (9):

$$a'_{1if} = \pi^{12}_f a'_{2if} + \varepsilon^{12}_{if} \quad (11)$$

where π^{12}_f is the factor-productivity of country 2 for factor f in terms of country 1. This procedure obtains international productivity differences for all binary combinations of countries rather than simply for each relative to the United States. These factor productivities are also

⁹ This specification is different from that in Hakura (2001) because she used each country's actual technology to measure factor contents of trade ($F_1 = A_1(I-B_1)^{-1}T_1$ and $F_2 = A_2(I-B_2)^{-1}T_2$).

estimated using SUR for each country pair. Using equations (10) and (11), the pair-wise HOV model with factor-productivity adjustment follows:¹⁰

$$F_1 - \alpha F_2 = \Pi_{12} V_1 - \alpha V_2 \quad (12)$$

Here Π_{12} is a diagonal $F \times F$ matrix with elements that are the corresponding productivity coefficients (π^{12}_j) estimated from equation (11). The difference $F_1 - \alpha F_2$ is the measured relative factor contents of trade with country 2's technology ($F_1 = A_2(I - B_2)^{-1} T_1$ and $F_2 = A_2(I - B_2)^{-1} T_2$).

Testing procedures are the same as for the basic HOV model.

3. Empirical Results

Estimating factor-productivity parameters from equations (9) and (11) requires data on actual technologies for multiple countries. Thus, we assembled a comprehensive data set for a group of 15 OECD countries, as described in Appendix A. There are two factors (physical capital and aggregate labor) and 23 industrial sectors. The dataset is similar to that in Hakura (2001) who developed a 23-sector dataset of four European countries with seven factors.

Because we combine input-output tables from different sources (OECD and Eurostat) in order to increase the number of countries, we were forced to aggregate to 23 sectors to maintain consistency in classification.¹¹ Aggregation is inevitable but raises the risk of systematic bias in the HOV predictions, a problem in all such studies (Feenstra and Hanson, 2000).

¹⁰ Derivation of the relative HOV model with factor-productivity adjustments is as follows. We have the productivity equation: $A_1(I - B_1)^{-1} = \Pi_{12} A_2(I - B_2)^{-1}$. Using the relationship for country 1, we have two equations: (1) $\Pi_{12} A_2(I - B_2)^{-1} T_1 = V_1 - \Pi_{12} A_2(I - B_2)^{-1} s_1 C_1$ and (2) $A_2(I - B_2)^{-1} T_2 = V_2 - A_2(I - B_2)^{-1} s_2 C_2$. Pre-multiplying (1) with Π_{12}^{-1} and (2) with α , and taking the difference between the two gives equation (12).

¹¹ Overall there are 23 industries in the OECD STAN database. However, because the figures on gross fixed capital formations (GFCF) contain residential (housing) investments for some countries, the GFCF values for agriculture (sector 1) and finance, insurance, and real estate (sector 22) are contaminated by residential investments. As noted in Appendix A, we were able to adjust the GFCF values for sector 22 but not for agriculture, which we exclude for factor-productivity estimation.

3.A. Factor-Augmenting Productivity Estimates

Table 1 reports the estimated factor-productivity parameters and associated statistics for equation (9), where factor efficiencies are defined relative to the United States. All factor productivities are positive and statistically significant.¹² The coefficients on physical capital for all 14 OECD countries are lower than unity, suggesting that the United States has the highest levels of capital productivity. Regarding labor, workers in Belgium, France, and Italy are more productive than those in the United States. For each country the R-squared coefficients measure the strength of the correlation between countries. In most cases the factor productivities fit well. For example, the R-squares for Canadian capital and labor are 0.847 and 0.590, indicating a strong concordance between Canadian and U.S. technologies. However, if the technology differed in a more complex way, as Davis and Weinstein (2001) suggested, there are additional determinants that the basic approach taken here does not account for. This might be the case for capital productivities in Belgium, France and Japan, which do not correlate well with the U.S. technology.

It is of interest to compare the national factor-productivity parameters developed using Trefler's (1993) method (equation (7)) and those using the method of Maskus and Webster (1999) in equation (9). In Table 2 we list the parameters computed from Table 1 (the first two columns) and those in Trefler's paper (the next pair of columns). The correlations between the corresponding factors are very high, at 0.81 for physical capital and 0.96 for aggregate labor. Thus, Trefler's estimated factor-productivities are similar to those obtained from estimation based only on unit factor requirements.

In addition, we compare these factor productivities with total factor productivities (TFP), which are estimated from a Cobb-Douglas production function applied to 13 manufacturing

¹² In fact, all are significantly different from both zero and unity at the five percent level.

sectors in these OECD countries.¹³ The correlations between TFP and individual factor productivities are not perfect (around 0.6) and the values of TFP generally lie between those for capital and labor. This would suggest that the empirical success of the factor-productivity adjustments in Trefler (1993) are attributable to systematic productivity differences across factors that the Hicks-neutral form (e.g., TFP) cannot account for. This confirms previous findings in the literature that Hicks-neutral productivity adjustments usually do not overturn the failures of the HOV equation.

3.B. Performance of the HOV Models

Table 3 shows the results of testing the HOV model with and without factor-productivity adjustments. The standard HOV model performs poorly as expected. The sign fit is 56.7 percent for our two factors, the slope is 0.021, and the variance ratio is 0.002. Though the sign fit is marginally better than a coin-flip, the slope and variance ratio tests indicate significant missing trade. Therefore, the results strongly reject the standard HOV model.

However, once the estimated factor productivities are introduced, these numbers improve considerably. For the HOV specification, as shown in the bottom panel, the sign fit improves to 76.7 percent, the slope coefficient rises to 0.231, and the variance ratio increases to 0.233. Furthermore, Figures 1-1 and 1-2 depict the correlation between factor productivities and factor prices as in equation (6). Both labor and capital fit well, with the correlation for aggregate labor being 0.78 and that for physical capital being 0.79.¹⁴

Regarding the pair-wise HOV model, Table 3 also shows a considerable improvement when factor-productivity adjustments are incorporated. The sign test improves from 54.8 percent

¹³ These functions are estimated in Nishioka (2006)

¹⁴ We obtain the factor prices from total compensation for each factor divided by total amount of the corresponding factors. Compensation for physical capital is derived as value added minus labor compensation.

to 71.9 percent and the variance ratio improves from 0.131 to 0.594. These positive improvements from the pair-wise models suggest that the acceptable performance of Trefler's factor-productivity adjustments was not simply spurious.

3.C. Characteristics of Factor Productivity

While introducing factor-productivity parameters (π_{cf}) is a convenient method to modify the HOV model, the interpretation of π_{cf} is not entirely clear. Suppose that workers in Belgium have the highest labor productivity. Then it could be that: (1) workers in Belgium simply work harder than workers in other countries; (2) workers in Belgium are no more industrious as workers elsewhere but they have access to technologies that make them more efficient; or (3) the simple number of workers cannot account for the difference in each worker's efficiency occurring from educational attainment (i.e., the human-capital approach).

We are particularly interested in the second possibility because our aggregate labor flows have been adjusted by working hours. Under the second notion we expect that labor productivity correlates positively with capital abundance.¹⁵ As shown in Figures 2-1 and 2-2, this feature characterizes the data, but weakly in an absolute sense. Using unadjusted input requirements, capital-productivities decline with capital abundance (correlation equals -0.25) and labor productivities rise with capital abundance (correlation equals 0.24). One reason for these correlations to be weak might be the limitation of our data to just two factors, with other elements such as knowledge capital and human capital being partially responsible for varying productivities.

¹⁵ This link was previously discussed by Dollar, Wolff, and Baumol (1988) who find the systematic correlation between labor-productivity and capital-abundance with their factor-price equalization model.

However, when we incorporate the adjusted productivity ratios (π_{cL}/π_{cK}), they correlate strongly with corresponding factor endowments as shown in Figure 3. For example, capital-abundant Japanese workers are productive relative to Japanese capital because they have good access to abundant capital (machines and computers). It seems that Trefler's original explanation holds well in this "relative" sense. This observation suggests that, similar to the approach of Davis and Weinstein (2001), who adjusted technologies according to factor abundance, our adjusted factor productivities also capture the link between technology, productivity, and factor-abundance that the Hicks-neutral form cannot accommodate.

4. The Relative Factor Abundance Model and Factor Productivities

The strong correlation between factor abundance and factor productivity is particularly relevant to the relative factor-abundance model of Debaere (2003). Debaere developed a prediction of the factor content of trade for the HOV model that relates bilateral differences in endowments to bilateral differences in factor trade. Our objective here is to reexamine his conclusion that the trade of South-North country pairs is consistent with HOV but that of North-North country pairs is not. We show that Debaere's result is caused not only by South-North differences in factor endowments, which is the issue he emphasized, but also by South-North differences in factor productivity. Specifically, because unskilled labor, the abundant factor in the South, has limited access to skilled labor and capital, the productivity of unskilled workers there is systematically lower than that in the North. This difference is an additional important reason that only South-North country-pairs perform well in his examination of HOV.

4.A. Endowment-Related Productivity Biases

To develop Debaere's relative factor abundance model, take equation (4) with U.S. technologies and impose identical and homothetic preferences:

$$F_c = V_c - A_{US}(I - B_{US})^{-1} s_c Y_W \quad (13)$$

Divide both sides of equation (13) by the scalar expenditure share s_c to obtain:

$$F^*_c = V^*_c - A_{US}(I - B_{US})^{-1} Y_W \quad (14)$$

where $F^*_c = A_{US}(I - B_{US})^{-1} T_c = F_c/s_c$ and $V^*_c = V_c/s_c$. Now consider equation (14) for two countries, c and c' , and take the difference between their expressions:

$$F^*_c - F^*_{c'} = V^*_c - V^*_{c'} \quad (15)$$

Equation (15) may be expressed for a particular factor (f) and divided by the sum of factor endowments, $V^*_{cf} + V^*_{c'f}$:

$$\frac{F^*_{cf} - F^*_{c'f}}{V^*_{cf} + V^*_{c'f}} = \frac{V^*_{cf} - V^*_{c'f}}{V^*_{cf} + V^*_{c'f}} \quad (16)$$

Then, express equation (16) for another factor (f') and again take differences:

$$\begin{aligned} \frac{F^*_{cf} - F^*_{c'f}}{V^*_{cf} + V^*_{c'f}} - \frac{F^*_{c'f'} - F^*_{cf'}}{V^*_{c'f'} + V^*_{cf'}} &= \frac{V^*_{cf} - V^*_{c'f}}{V^*_{cf} + V^*_{c'f}} - \frac{V^*_{c'f'} - V^*_{cf'}}{V^*_{c'f'} + V^*_{cf'}} \\ \Leftrightarrow \frac{F^*_{cf} - F^*_{c'f}}{V^*_{cf} + V^*_{c'f}} - \frac{F^*_{c'f'} - F^*_{cf'}}{V^*_{c'f'} + V^*_{cf'}} &= \frac{2V^*_{c'f'}}{V^*_{c'f'} + V^*_{cf'}} \left(\frac{V^*_{c'f'}}{V^*_{c'f}} - \frac{V^*_{c'f'} + V^*_{cf'}}{V^*_{c'f} + V^*_{c'f'}} \right) \end{aligned} \quad (17)$$

Here, the relative difference in measured factor content of trade is on the left-hand side and the relative difference in predicted factor content of trade is on the right-hand side.

For any two factors f and f' , a country c is said to be relatively abundant in factor f compared to country c' when $V^*_{cf}/V^*_{c'f}$ is larger than $V^*_{c'f'}/V^*_{cf'}$. This statement is easily shown because the relative factor abundance relationship $V^*_{cf}/V^*_{c'f} > V^*_{c'f'}/V^*_{cf'}$ holds if and only if $V^*_{c'f'}/V^*_{c'f} > (V^*_{c'f'} + V^*_{cf'}) / (V^*_{cf} + V^*_{c'f})$, which is the right-hand side of the second equation in (17).

Therefore, the testing strategy is to check the sign concordance of measured and predicted relative differences in factor trade.¹⁶ Debaere showed that equation (17) holds for the case of Hicks-neutral productivity. We show in Appendix B that it holds also for the case of adjusted factor productivities.

Our tests using the 15-country OECD dataset are reported in Table 3, Panels 5 and 6. It is clear that adjusting endowments by factor productivities makes a critical difference in the performance of the relative HOV model. When factors are not adjusted, the sign match is less than 50 percent and the variance ratio is 0.056. However, once factors are adjusted by our estimated productivities, these statistics improve to 60 percent for the sign test and 0.943 for variance ratio.

To make a complete comparison, it is important to investigate this issue using the same data as Debaere. Because his dataset is the same as that in Trefler (1993), it is impossible to estimate appropriate factor productivities by using bilateral simple regressions as in equation (9) or equation (10). Our compromise is to use Trefler's method in equation (7) to obtain factor productivities.

A first step is to show theoretically that the relative factor abundance comparison ($V_{cf}^*/V_{cf'}^* > V_{c'f}^*/V_{c'f'}^*$) can be divided into two parts: (1) relative factor-productivity ratios; and (2) productivity-equivalent relative factor abundance. Denote factor endowments at the productivity-equivalent level as $V'_{cf} = \pi_{cf} V_{cf}^*$ and rewrite relative factor abundance as:

$$\frac{V_{cf}^*}{V_{cf'}^*} > \frac{V_{c'f}^*}{V_{c'f'}^*} \Leftrightarrow \frac{V'_{cf}/\pi_{cf}}{V'_{cf'}/\pi_{cf'}} > \frac{V'_{c'f}/\pi_{c'f}}{V'_{c'f'}/\pi_{c'f'}} \Leftrightarrow \frac{V'_{cf}}{V'_{cf'}} \frac{\pi_{cf'}}{\pi_{cf}} > \frac{V'_{c'f}}{V'_{c'f'}} \frac{\pi_{c'f'}}{\pi_{c'f}} \quad (18)$$

Equation (18) explains that the relative factor-abundance ratio without productivity adjustments ($V_{cf}^*/V_{cf'}^*$ or $V_{c'f}^*/V_{c'f'}^*$) is the product of the productivity-equivalent relative factor

¹⁶ Though Debaere (2003) reported only sign tests, we report slope tests and variance ratios as well.

abundance ratio (V'_{cf}/V'_{cf} or $V'_{c'f}/V'_{c'f}$) and the factor-productivity ratio (π_{cf}/π_{cf} or $\pi_{c'f}/\pi_{c'f}$). If, as Debaere assumed, the Hicks-neutral form ($\pi_{cf}/\pi_{cf} = \pi_{c'f}/\pi_{c'f}$) is realistic, then relative factor abundance and productivity-equivalent factor abundance are identical and his basic conclusion holds. However, if productivity adjustments are more general, then both elements matter. For example, if f is labor (L) and f' is physical capital (K) for the South ($c=S$) and the North ($c'=N$), we might expect labor in the South to be less productive than in the North because it operates with a smaller relative capital endowment. As a result, we have an inequality in relative productivity ratios: $\pi_{SK}/\pi_{SL} > \pi_{NK}/\pi_{NL}$ OR $\pi_{SK}/\pi_{NK} > \pi_{SL}/\pi_{NL}$.

It is important, therefore, to study South-North differences in factor productivities in addition to relative factor endowments. For this purpose, we use Trefler's dataset, divide countries into the South and the North according to Debaere (2003), and develop the South-North productivity ratios for factors. The parameters (π_{cf}) are obtained by estimating equation (7) for physical capital, skilled labor, unskilled labor, and aggregate labor. If Hicks-neutral productivity differences were realistic, we would expect these productivity ratios to be identical across any factor pair ($\pi_{cf}/\pi_{c'f} = \pi_{cf}/\pi_{c'f}$). However, this is not the case as shown in Figures 4-1 through 4-8. Rather, we find the interesting tendency that the productivity ratio of the South to the North for unskilled labor is always smaller than that for skilled labor and physical capital. There is not a similar tendency for the North-North pairs. Therefore, the systematic tendency in factor productivities supports the inequality in equation (18) only for the South-North country pairs of particular factor combinations: unskilled labor/skilled labor, unskilled labor/capital, and labor/capital. This evidence implies that Debaere's conclusion could be delivered by the interplay between endowment differences and factor-productivity differences.

4.B. Relation to other Explanations of Productivity Biases

Here we have attributed relative factor-productivity biases solely to differences in relative factor abundance.¹⁷ Clearly, however, there are other possible sources of these biases. In particular, capital-skill complementarity (Krusell et al., 2000) and imperfect substitutability between skilled labor and unskilled labor (Caselli and Coleman II, 2006) have been cited as important possibilities. Regarding capital-skill complementarity, our analysis of Trefler's dataset unearths an implication similar to that of Krusell et al. (2000). Specifically, capital productivity and skilled-labor productivity co-move with economic development. As seen in Figure 4-2, where most observations are in the lower left-hand corner, developing countries have lower relative productivity in both skilled labor and capital. In Figure 4.1, however, the observations are concentrated in the center, suggesting convergence of these productivities among the developed countries. If capital and skilled labor are complements, the higher productivity performance of skilled labor in the North might be associated with higher quality and sophistication of capital in the North. Our approach does not amount to a test of such complementarity, however.

On the other hand, as seen in Figures 4.4 and 4.6, the South's usage of unskilled labor is unproductive relative to the North's usage, regardless of the relative productivities of capital and skilled labor. This tendency of skill bias is quite different from the finding in Caselli and Coleman II (2006).¹⁸ They found evidence that developed countries use skilled labor more

¹⁷ Our approach is related to that in Acemoglu and Zilibotti (2001), who set out a model of factor-biased technological change as factor endowments vary, though their theory implies a constant ratio of factor productivities across countries.

¹⁸ Strictly speaking, the calculation of factor productivities for Caselli and Coleman II (2006) is different from ours even though both assume constant return to scale production functions. Caselli and Coleman II estimated country-level production functions with a constant-elasticity-of-substitution (CES) aggregate of labor types: $y = K^\alpha [AuLu]^\sigma + [AsLs]^\sigma]^{(1-\alpha)/\sigma}$ where Au and As are factor-augmenting productivities for unskilled-labor and skilled-labor, respectively. They calibrated these productivities by introducing the condition that skill premium equals relative

efficiently and developing countries use unskilled labor more efficiently. They explained this cross-country pattern of skill bias by imagining two different technologies to produce aggregate output. One is an assembly line where unskilled labor worked with the supervision of just a few skilled workers. The other is a computer-controlled facility run solely by skilled workers while unskilled labor engages in janitorial work. They argue that the South chooses the first prototypical technology and the North chooses the second. Therefore, unskilled labor in the South is absolutely more productive.

We suggest two explanations why the dataset we use does not support this view, finding instead that unskilled labor is unproductive in the South. First, as we explain in the data Appendix, our unskilled labor consists of clerical, service, sales, agriculture, and production workers based on the International Standard Classification of Occupations, while skilled labor comprises managerial and technical occupations. In essence, our definition assigns unskilled labor to “blue collar” labor engaged in basic production activities. In this sense, it would be more accurate to describe this category as “low skilled”, for such workers may have achieved secondary education and learned numerous skills from job experience. In contrast, Caselli and Coleman II conceive of unskilled workers solely as support laborers with minimal education, based on the categorization in Barro and Lee (2001). In their preferred dataset, unskilled workers have no education or only a few years of primary education. They consider all workers that completed at least primary education to be skilled. With this definition their unskilled labor measure amounts to less than three percent of the labor force for the United States

Second, because of data limitations, we could not adjust Trefler’s dataset to reflect international differences in educational attainment. Even in jobs for production facilities,

marginal products of skills: $ws/wu = (As/Au)^\sigma(Ls/Lu)^{(\sigma-1)}$, and by using data measuring Ls , Lu , ws/wu , and parameters $\sigma=1/3$, $1/(1-\sigma)=1.4$.

workers with higher education might be employed in developed countries more intensively than in developing countries. Our inability to adjust for education (human capital) might affect our estimates of factor productivities based on occupational differences.¹⁹ Thus, a useful subject for future research would be to combine the Barro-Lee data on detailed educational achievement and wages with the HOV equations.

5. Concluding Remarks

In this paper we reexamine Trefler's (1993) basic factor-productivity model. Departing from his procedure, we estimate factor-productivity parameters from each country's actual technologies. This approach permits use of the standard evaluations of the HOV model (sign test, slope test, and variance ratio test). Using a dataset of fifteen OECD countries, we find evidence supporting the fundamental idea of factor-augmenting productivities, with both the sign concordance and the variance ratio increasing markedly. Our results indicate that factor-augmenting productivity differences are an appropriate modification of HOV models.

Prior studies that made technological specifications increasingly more flexible by using country-specific data also supported the extended HOV model (Hakura, 2001; Davis and Weinstein, 2001). Indeed, Davis and Weinstein (2001) established a strong fit of the HOV equations when technologies are modified across both industries and countries according to factor abundance. The contribution here is to show that a simpler modification – factor augmentation that is neutral across industries – can establish considerable gains in the predictive performance of the HOV model.

More fundamentally, the analysis unearthed a particular feature of factor productivities in both the OECD dataset and Trefler's dataset. Specifically, factor productivities are inversely

¹⁹ Maskus and Webster (1999) defend the use of occupational categories for HOV modeling.

correlated with own-factor endowments and positively correlated with other factor endowments, which is consistent with the neoclassical trade model without FPE due, say, to specialization within different cones. This is especially the case as regards labor in developing countries. As a result, Debaere's (2003) finding that South-North factor trade may be explained well by the relative HOV model with Hicks-neutral productivity differences needs to be supplemented by the interplay between relative endowments and factor productivities.

References

- Acemoglu, Daron and Fabrizio Zilibotti (2001), "Productivity Differences," *Quarterly Journal of Economics* 116, pp 563-606.
- Antweiler, Werner and Daniel Trefler (2002). "Increasing Returns and All That: A View from Trade," *American Economic Review* 92, pp 93-119.
- Barro, Robert J. and Jong-Wha Lee (2001). "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers* 53, pp 541-563.
- Bowen, Harry Edward E. Leamer, and Leo Sveikauskas (1987). "Multicountry, Multifactor Tests of the Factor Abundance Theory," *American Economic Review* 77, pp 791-809.
- Caselli, Francesco and Wilbur John Coleman II (2006). "The World Technology Frontier," *American Economic Review* 96, pp 499-522.
- Conway, Patrick (2002). "The Case of the Missing Trade and Other Mysteries: Comment," *American Economic Review* 92, pp 394-404.
- Davis, Donald and David Weinstein (2001). "An Account of Global Factor Trade," *American Economic Review* 91, pp 1423-1453.
- Davis, Donald, David Weinstein, Scott Bradford, and Kazushige Shimpo (1997). "Using International and Japanese Regional Data to Determine When the Factor Abundance Theory of Trade Works," *American Economic Review* 87, pp 421-446.
- Debaere, Peter (2003). "Relative Factor Abundance and Trade," *Journal of Political Economy* 111, pp 589-610.
- Dollar, David, Edward N. Wolff, and William J. Baumol (1988). "The Factor-Price Equalization Model and Industry Labor Productivity: An Empirical Test across Countries," in Robert C. Feenstra, ed., *Empirical Methods for International Trade*. Cambridge, MA: MIT Press, pp 23-47.
- Dornbusch, Rudiger, Stanley Fischer, and Paul A. Samuelson (1980). "Heckscher-Ohlin Trade Theory with a Continuum of Goods," *Quarterly Journal of Economics* 95, pp 203-224.
- Feenstra, Robert C. and Gordon Hanson (2000). "Aggregation Bias in the Factor Content of Trade: Evidence from U.S. Manufacturing," *American Economic Review* 90, pp 155-160.
- Fitzgerald, Doireann and Juan Carlos Hallak (2004). "Specialization, Factor Accumulation and Development," *Journal of International Economics* 64, pp 277-302.
- Gabaix, Xavier (1997). "The Factor Content of Trade: A Rejection of the Heckscher-Ohlin-Leontief Hypothesis," Harvard University, Department of Economics, manuscript.

Hakura, Dalia (2001). "Why Does HOV Fail? The Role of Technological Differences within the EC," *Journal of International Economics* 54, pp 361–382.

Helpman, Elhanan (1999). "The Structure of Foreign Trade," *Journal of Economic Perspectives* 13, pp 121-144.

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

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

Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull, and Giovanni L. Violante (2000). "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica* 68, pp 1029-1053.

Leamer, Edward E. (1984). *Sources of International Comparative Advantage: Theory and Evidence*, Cambridge, MA: MIT Press.

Leontief, Wassily (1953). "Domestic Production and Foreign Trade: The American Capital Position Re-examined," *Proceedings of the American Philosophical Society* 97, pp 332-349.

Maskus, Keith E (1985). "A Test of the Heckscher-Ohlin-Vanek Theorem: The Leontief Commonplace," *Journal of International Economics* 19, pp 201-212.

Maskus, Keith E. and Allan Webster (1999). "Estimating the HOV Model with Technology Differences Using Disaggregated Labor Skill for the United States and the United Kingdom," *Review of International Economics* 7, pp 8-19.

Nishioka, Shuichiro (2006). "An Explanation of OECD Factor Trade with Knowledge Capital and the HOV Model," University of Colorado, Department of Economics, manuscript.

Staiger, Robert M., Alan V. Deardorff, and Robert M. Stern (1987). "An Evaluation of Factor Endowments and Protection as Determinants of Japanese and American Foreign Trade," *Canadian Journal of Economics* 20, pp 449-463.

Trefler, Daniel (1993). "International Factor Price Differences: Leontief was Right!" *Journal of Political Economy* 101, pp 961-987.

Trefler, Daniel (1995). "The Case of the Missing Trade and Other Mysteries," *American Economic Review* 85, pp 1029-1046.

Trefler, Daniel (2002). "The Case of the Missing Trade and Other Mysteries: Reply," *American Economic Review* 92, pp 405-410.

Appendix A: Construction of Data

1) Input-Output Data

Input-output tables (total use) for Australia (1994-1995), Canada (1997), Denmark (1997), Finland (1995), France (1995), Germany (1995), Japan (1997), the Netherlands (1997), Norway (1997), the United Kingdom (1998), and the United States (1997) are from the OECD input-output database for 2002. Belgium (1995), Italy (1995), Spain (1995), and Sweden (1995) are from the Statistical Office of the European Communities (Eurostat). The I-O tables from the OECD database employ ISIC Rev.3 classification containing 41 industrial groups and the I-O tables from the Eurostat employ NACE/CLIO classification containing 59 groups. These two classifications are aggregated into 23 industrial groups of ISIC Rev.3. The number of industrial groups is smaller than the 35 sectors used by Davis and Weinstein (2001) but is the same as Hakura (2001). The input-output matrices and final consumption, gross output, and net exports are derived from the I-O tables for 1997. Final consumption is the sum of final consumption of households, final consumption and investment of government, gross fixed capital formation, and changes in inventory.²⁰ Therefore, the total use table of country c always satisfies the equation: $T_c = (I - B_c)Q_c - C_c$ where B_c is a 23×23 indirect technology matrix for the unit intermediate requirements and $(I - B_c)Q_c$ vector equals net output (Y_c). B_c is obtained by taking input-output data from the I-O tables and dividing inputs in each sector by the corresponding sector's gross output.²¹ To convert the dataset into U.S. dollars, we use purchasing power parities (1997) from the Penn World Table version 6.2 (Heston, Summers and Aten) and the OECD *Economic*

²⁰ Finland's data required adding discrepancies in final consumption in order to maintain consistency of the I-O table.

²¹ In the case of two sectors, the input usage matrix can be obtained as following.

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

Outlook (2006). Conway (2002) and Trefler (2002) discuss the choice between purchasing power parity (PPP) and nominal exchange rates. For Australia, Belgium, Finland, France, Germany, Italy, Sweden, Spain, and the United Kingdom, nominal values in the I-O tables are uniformly multiplied by the growth rates of total nominal GDP to adjust differences from year 1997.

Table A: Sectors of Industrial Activities

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

2) Factor Endowment Data

(A) Physical Capital Stock

Capital stock is developed by the perpetual inventory method (e.g., Keller, 2000). Values for gross fixed capital formation (GFCF) are derived from the OECD structural analysis (STAN) database (2004) and unreported data are estimated from the ISIC Rev.2 version of the OECD STAN database (1995, 1997, and 1998) and the Eurostat. As many GFCF data as possible are derived from these databases but there are still some unavailable data. The following procedure

is taken to interpolate these data. First, some detailed sectors (e.g., 15 and 16) are unavailable but data for their aggregated (15+16) industry exist for certain years. We use the share of the nearest year to allocate those totals to each detailed sector. Second, for Denmark some of the aggregate industry totals were also unavailable, and we use the average growth rates of the nearest four years to interpolate the unreported data.

One major problem with using GFCF data from the OECD STAN database (2004) is that some countries include residential investments but other countries do not. In particular, agriculture (sector 1) and finance, insurance, and real estate (sector 22) are the main sources of errors from residential investments. To avoid serious errors, we first deflate nominal values of the real estate sector's GFCF by 65 percent²² for countries in the dataset except Canada, Japan, the United Kingdom, and the United States. Figures for total nonresidential GFCF are separately obtained from the OECD *National Account Statistics* (2006) and allocated to each sector according to the shares developed from the OECD STAN database.²³ Unfortunately, it is impossible to adjust agriculture for residential investment and caution must be exercised when data from that sector are used in the analysis.

To convert GFCF figures into real series, deflators for nonresidential business investment from the OECD Economic Outlook (2006) are used. After converting into a real local currency series, we compute real capital stock data with the perpetual-inventory method, using a depreciation rate of 0.1333 (e.g., Leamer, 1984; Bowen, Leamer, and Sveikauskas, 1987; and Davis and Weinstein, 2001). Then, the real capital stock is converted into 1997 U.S. dollars by purchasing power parities. For Japan, sectoral GFCF data are unavailable from the OECD

²² Based on the Japanese value.

²³ We use the dataset developed from the OECD STAN database directly for Belgium. In the case of Norway, to separate "housing investment" from "other construction," we use the corresponding shares from Finland and Sweden.

STAN database (2004). Therefore, we take the total GFCF series from the OECD *National Accounts Statistics* (2006) and Japan's sectoral shares are obtained from the nominal investment matrix tables of the ESRI-Histat database.

(B) Labor

Sectoral labor inputs (total employment) are derived from the OECD STAN databases (1998 and 2004), the Eurostat, and the OECD *Employment by Activities and Status* (2006). To interpolate unreported data, we use the available share of the nearest year to allocate aggregated sector totals to each detailed sector. Country-level average working hours from the OECD *Employment and Labor Market Statistics* (2006) are used to adjust international differences in average working hours, normalized by U.S. working hours.

Appendix B: Relative Abundance and Factor-Productivity Adjustment

Here we introduce factor-augmenting productivity to the right hand side of equation (17). First, in the following equation we show that the inequality in relative factor abundance for the factor-productivity model does not coincide with that for the strict (or Hicks-neutral) model. Thus, the empirical prediction of Debaere's model with factor-productivity parameters differs from Debaere's original specification.

$$\frac{V^*_{c'f'}}{V^*_{c'f}} > \frac{V^*_{cf'}}{V^*_{cf}} \Leftrightarrow \frac{\pi_c V^*_{c'f'}}{\pi_c V^*_{c'f}} > \frac{\pi_c V^*_{cf'}}{\pi_c V^*_{cf}} \neq \frac{\pi_{c'f'} V^*_{c'f'}}{\pi_{c'f'} V^*_{c'f}} > \frac{\pi_{cf'} V^*_{c'f'}}{\pi_{cf'} V^*_{cf}}$$

Proof of the relative factor-abundance model with factor-augmenting productivities is following:

$$\begin{aligned}
\frac{\pi_{c'f'}V_{c'f'}^*}{\pi_{c'f}V_{c'f}^*} > \frac{\pi_{c'f'}V_{c'f'}^*}{\pi_{c'f}V_{c'f}^*} &\Leftrightarrow \pi_{c'f'}V_{c'f'}^* \pi_{c'f}V_{c'f}^* > \pi_{c'f}V_{c'f}^* \pi_{c'f'}V_{c'f'}^* \\
&\Leftrightarrow \pi_{c'f'}V_{c'f'}^* \pi_{c'f}V_{c'f}^* + \pi_{c'f'}V_{c'f'}^* \pi_{c'f}V_{c'f}^* > \pi_{c'f'}V_{c'f'}^* \pi_{c'f}V_{c'f}^* + \pi_{c'f}V_{c'f}^* \pi_{c'f'}V_{c'f'}^* \\
&\Leftrightarrow \frac{\pi_{c'f'}V_{c'f'}^* (\pi_{c'f}V_{c'f}^* + \pi_{c'f'}V_{c'f'}^*)}{\pi_{c'f}V_{c'f}^* (\pi_{c'f}V_{c'f}^* + \pi_{c'f'}V_{c'f'}^*)} > 1 \\
&\Leftrightarrow \frac{\pi_{c'f'}V_{c'f'}^*}{\pi_{c'f}V_{c'f}^*} > \frac{\pi_{c'f}V_{c'f}^* + \pi_{c'f'}V_{c'f'}^*}{\pi_{c'f}V_{c'f}^* + \pi_{c'f'}V_{c'f'}^*}
\end{aligned}$$

where $\pi_{c'f}$ is the factor-productivity parameter for factor f of country c .

Tables and Figures

Table 1: The Results of SUR estimations

	Physical Capital			Aggregate Labor		
	π_{cf}	s.e. of π_{cf}	r-square	π_{cf}	s.e. of π_{cf}	r-square
Australia	0.706	0.029	0.758	0.780	0.028	0.662
Belgium	0.660	0.054	0.105	1.127	0.022	0.896
Canada	0.761	0.024	0.847	0.859	0.034	0.590
Denmark	0.654	0.022	0.822	0.867	0.038	0.476
Finland	0.644	0.036	0.563	0.766	0.026	0.692
France	0.817	0.063	0.211	1.079	0.043	0.591
Germany	0.702	0.027	0.788	0.858	0.031	0.666
Italy	0.692	0.031	0.691	1.084	0.032	0.740
Japan	0.505	0.040	0.158	0.733	0.030	0.546
Netherlands	0.702	0.037	0.548	0.926	0.033	0.607
Norway	0.598	0.029	0.667	0.990	0.038	0.625
Spain	0.614	0.039	0.438	0.721	0.021	0.774
Sweden	0.803	0.038	0.663	0.861	0.027	0.738
UK	0.737	0.042	0.517	0.739	0.033	0.457

Note: (1) Dependent variables are the US technology
(2) Sector 1 "Agriculture" is excluded

Table 2: Estimated Factor Augmenting Productivities

	Maskus and Webster (1999)		Trefler (1993)		TFP (5)
	(1) capital	(2) labor	(3) capital	(4) labor	
Australia	0.706	0.780	0.707	0.819	0.655
Belgium	0.660	1.127	0.641	1.072	0.911
Canada	0.761	0.859	0.852	0.861	0.945
Denmark	0.654	0.867	0.800	0.931	0.705
Finland	0.644	0.766	0.620	0.726	0.670
France	0.817	1.079	0.739	1.085	0.953
Germany	0.702	0.858	0.664	0.919	0.811
Italy	0.692	1.084	0.655	1.057	0.782
Japan	0.505	0.733	0.510	0.778	0.634
Netherlands	0.702	0.926	0.683	0.931	0.965
Norway	0.598	0.990	0.711	1.011	0.809
Spain	0.614	0.721	0.589	0.739	0.659
Sweden	0.803	0.861	0.758	0.850	0.793
UK	0.737	0.739	0.898	0.809	0.839
US	1.000	1.000	1.000	1.000	1.000
(1)	1.000	0.349	0.811	0.346	0.687
(2)	-	1.000	0.155	0.964	0.644
correlations (3)	-	-	1.000	0.228	0.592
(4)	-	-	-	1.000	0.643
(5)	-	-	-	-	1.000

Notes: 1) Maskus and Webster (1999) use SUR model. See equation (9).

2) U.S. technology is the explanatory variable for Maskus and Webster.

3) TFP is estimated from CRS Cobb-Douglas production function for 13 manufacturing sectors (exclude "coke, refined petroleum products and nuclear fuel").

Table 3: Results of the HOV Models

I. Strict Models							
	1. The HOV Model			3. The Pairwise HOV Model			5. The Relative HOV Model
	2 factors	capital	labor	2 factors	capital	labor	Capital-Labor
Sign Test	0.567	0.667	0.467	0.548	0.638	0.457	0.438
Slope Test	0.021	0.021	0.019	0.057	0.057	-0.215	0.092
standard error	0.008	0.012	0.020	0.025	0.035	0.039	0.021
R-squared	0.183	0.173	-0.003	0.010	-0.004	0.175	0.160
Variance Test	0.002	0.002	0.006	0.131	0.130	0.193	0.056

II. With Factor Productivity Adjustments							
	2. The HOV Model			4. The Pairwise HOV Model			6. The Relative HOV Model
	2 factors	capital	labor	2 factors	capital	labor	Capital-Labor
Sign Test	0.767	0.733	0.800	0.719	0.695	0.743	0.600
Slope Test	0.231	0.231	0.035	0.376	0.376	0.454	0.514
standard error	0.079	0.114	0.090	0.046	0.066	0.086	0.081
R-squared	0.218	0.209	-0.057	0.227	0.216	0.161	0.280
Variance Test	0.233	0.230	0.107	0.594	0.596	0.917	0.943

Notes: 1) The HOV model refers to the testing method in Trefler (1995).

2) The Pairwise HOV model refers to the testing method in Hakura (2001).

3) The Relative HOV model refers to the testing method in Debaere (2003).







