

Consistent Cross-Country Estimates of Labor Productivity
By Kathryn G. Marshall

California Polytechnic State University

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October 2009

In this paper I examine the evidence for productivity-adjusted factor price equalization across a diverse sample of 33 countries. I use the U.S. technology matrix combined with conforming output from the OECD input-output tables to construct a precise index of factor-specific productivity for capital and three types of labor. I compare these productivities to factor payments inferred from the input-output value-added payments, and soundly reject the hypothesis of productivity-adjusted FPE for both capital and labor. I then put forth and test an alternative hypothesis that productivity differences stem for industry-specific variations in total factor productivity combined with strong complimentary use of factors in most industries. The alternative model does well in some respects but there remain idiosyncratic differences in technology which are difficult to assess due to data limitations.

JEL CLASSIFICATION: F16, J24, J31, O15

1. Introduction

There remains a wide dispersion in wages across the world even after the wave of globalization during the last several decades. In the year 2000, workers in Brazil earned on average \$6,000 a year while those in the U.S. earned on average \$46,000.¹ In his seminal study of factor price differences across countries, Trefler (1993) proposed a simple explanation for the disparity in wages across countries: factor price differences reflect international differences in the productivity of factors. More recently, Maskus and Nishioka (2008) confirm Trefler's insight that productivity-adjusted endowments correctly predict the direction and volume of trade between country pairs, and Hanson and Slaughter (2002) show that productivity differences explain wage differences across U.S. states. The evidence examined in this study suggests that wage differences are closely associated with productivity differences for skill-adjusted measures of labor across a diverse set of 33 countries. However, the specific relationship suggests that a factor-specific and industry-neutral explanation for productivity differences is too limited. Instead, I argue that differences in factor-specific productivities stem largely from underlying differences in total factor productivity between industries combined with less than unit elasticity of substitution between factors.

Based on detailed OECD input-output data now available for a wide range of countries, Fisher and Marshall (2008) establish that technology differences are too complex to be captured by factor-specific differences in productivity, but these input-output data only allow a single aggregate measure of labor. An obvious source of differences in labor productivity between countries at different levels of development is differences in the skill composition of the labor

¹ All wage data in this study are computed from OECD input-output value-added data converted by the International Comparison Project's purchasing power parity exchange rates. Please see the Appendix for further details.

force. This study incorporates three broad aggregates of labor intended to reflect skills of the labor force combined with the extensive OECD input output data. A simple index of factor-specific productivity relative to the U.S. is constructed, and the results are compared to factor payments constructed from the input-output data itself. This method assures a highly consistent measure of factor usages and factor payments for both labor and capital which allows for a precise test of productivity adjusted factor price equalization. A strong rejection of this test in turn suggests that differences in factor productivity are complex and industry specific.

An alternative explanation for differences in technology between countries is rooted in differences in total factor productivity (TFP). Hall and Jones (1999) and Parente and Prescott (2000) have established that differences in total factor productivity in an aggregate production function explain wide disparities in income per worker across countries. Harrigan (1997) and Lai and Zhu (2007) have also established that TFP differs significantly between industries. I present a simple general equilibrium model of technology differences based on an industry-specific constant elasticity of substitution (CES) production function that allows variations in TFP between industries. To test this model I construct technology matrixes for 30 countries at a fourteen sector level of aggregation. I show that a pattern of uneven technological progress reflected in the relatively higher TFP of capital intensive industries in low wage countries, combined with less than unit elasticity of substitution between factors, can help explain the observed pattern of factor price differences.

The next section elaborates the data and methodology used to measure average differences in factor usage across industries and presents the results of these measures. The subsequent section considers the relationship between factor payments and factor usage. This is

followed by a more careful analysis of industry specific difference in technologies and a brief conclusion.

2. Measurement of factor-specific differences in productivity

Factor-specific differences in productivity are defined by a technology matrix which describes the direct and indirect use of factors of production across different industries. Let A_c be the f by n technology matrix for country C , where f is the number of factors and n is the number of industries. The factor input used for one unit of output in country C can be compared to that of a reference country R such that $\pi_{fic} a_{fic} = a_{fiR}$, where π_{fic} is the factor-specific difference in productivity for industry i . Factor-specific but industry neutral differences in productivity imply $\pi_{fic} = \pi_{ffc}$ for all industries, so the factor specific productivity is denoted simply by π_{fc} .

Even if the theoretical justification put forward by Trefler (1993) is correct for factor-specific differences in technology, there is likely to be some empirical variation in this measure across industries between two countries. Furthermore it is often difficult to obtain accurate data on the technology matrix for many countries, especially for a detailed specification of factor use by industry across the entire economy. I propose a simple measure of π_{fc} that both allows for across industry variation and can be measured with only the reference country technology matrix, assuming data on the total endowments of comparison countries are available, designated by the vector v_c . Define the virtual endowment \tilde{v}_c as the vector of factors that would be used by the reference country to produce country c 's output, so that $\tilde{v}_c = A_R y_c$. The factor specific

productivity can then be computed by $\pi_{fc} = \frac{\tilde{v}_{fc}}{v_{fc}}$, where \tilde{v}_{fc} and v_{fc} are the f^{th} elements in the respective endowments vectors. Let Π_c represent a f by f diagonal matrix with the diagonal elements equal to the constructed productivity measure π_{fc} for each factor.

The factor specific productivity measure constructed in this fashion is essentially an index measure of the difference in factor usage across sectors between the reference country and comparison countries. The weights of the index are the output vectors of each comparison country. If the difference in factor usage is uniform across sectors, the index will correspond to the factor specific-productivity differences suggested by Trefler (1993). Only in this special case will $\Pi_c A_c = A_R$. In the more general case that industries vary in their use of factors across countries, then $\Pi_c A_c \neq A_R$, although by construction $\Pi_c A_c y_c \equiv A_R y_c$. The index measure gives a larger weight to larger sectors in the economy, and therefore is a more accurate economy-wide average of differences in factor usage when these uses are not uniform between industries.

2.1. Data Issues

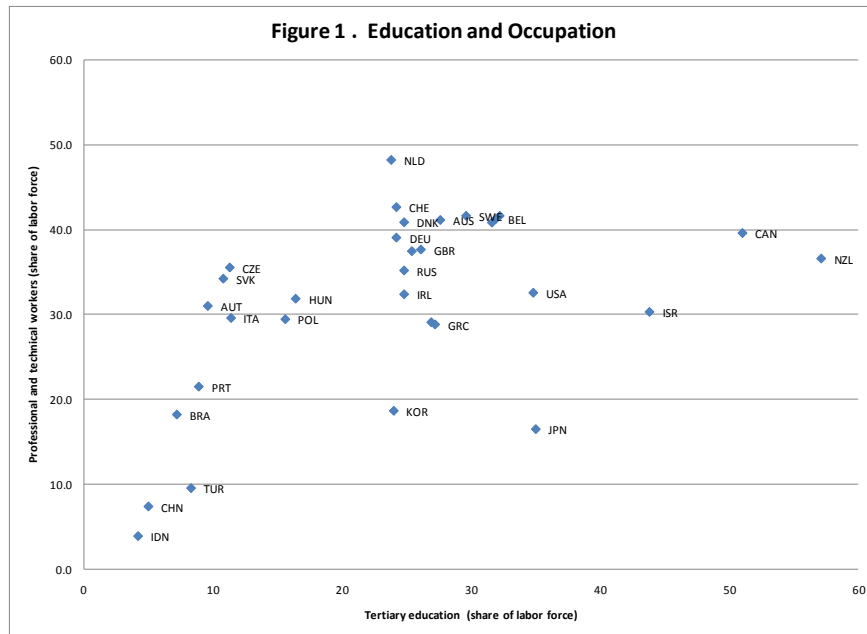
Factor-specific differences in productivity presume that exogenous factors can be defined and measured across countries. The United States is chosen as the reference country because it has detailed data on labor usage by sector for different occupation categories. However, occupation categories are not necessarily ideal because they are to some degree endogenously defined, and the choice of occupational category rather than education level is imposed by data limitations. For comparison countries, the International Labor Organization publishes occupational employment data for most countries based on the 1988 International Standard Classification of Occupations (ISCO-88). The U.S. Bureau of Labor Statistics publishes detailed

occupation by industry data but it is based on its own Standard Occupational Classification (SOC) system that does not readily correspond to the ISCO-88 at a disaggregated level. A much closer correspondence between the two typologies is achieved by aggregating labor into three broad categories: professional and technical, sales and services, and production workers. (An exact correspondence table is given in the data appendix.)

The composition of the U.S. workforce in comparison to the other countries in the sample is summarized in Table 1. The two most notable features are the high share of sales and service workers in the U.S. compared to both high and low wage countries, and the high share of production workers in low wage countries, where they make up over 50 percent of the workforce. There is a reasonably strong correlation between the share of the labor force with tertiary education and the share of professional and technical workers in the labor force, as illustrated in Figure 1.

Table 1. Composition of labor force by labor category

	Professional and Technical	Sales and Service	Production
United States	34%	39%	28%
20 High Wage Countries			
Average	36%	28%	36%
Standard Deviaton	7%	5%	5%
12 Low wage Countries			
Average	23%	23%	54%
Standard Deviaton	10%	8%	12%
All Countries			
Average	31%	27%	42%
Standard Deviaton	11%	7%	12%



The computation of a virtual endowment requires conformable output by industry for all countries and the technology matrix for the reference country. The OECD input-output data for the year 2000 is used for 33 countries, a sample which includes 21 high wage countries and 11 low wage countries. Local currency values are converted to U.S. dollars using the International Comparison Project’s purchasing power parity exchange rates.

Factor-specific productivities have important implications for factor prices, but data on factor prices is also hard to come by. I use the value-added data to infer factor payments for both aggregate labor and capital, given measures of the stock of labor and capital. For example, the average wage in Brazil is computed by dividing by the total value-added paid to labor by the Brazil’s total employed labor force measured in person years. Likewise, the rental rate paid to capital in Brazil is determined by dividing total payments to capital by Brazil’s estimated capital stock. (Please see the Appendix for details on data sources and computation of labor and capital stocks.) The resulting factor payments (reported in Appendix Table 1) are thus consistent with the output by sector for each country, also taken from the OECD data.

2.2. Empirical results

It is well established that countries at different levels of economic development have very different levels of labor productivity as measured by output per worker. An important question is whether these differences stem from a different combination of labor force skills or whether labor-specific productivity is lower in a uniform way across all labor skills. The virtual endowments-based measure of labor productivity presented in Figure 2 confirm that by and large differences in labor specific productivity are strongly correlated across labor types. The productivity of professional and technical workers relative to the U.S varies from a high of 1.21 for Japan to a low of 0.21 for China. For production workers the range is even greater, going from a high of 1.27 for Denmark to a low of 0.04 for China.

Figure 2. Index of factor-specific productivity for 3 types of labor

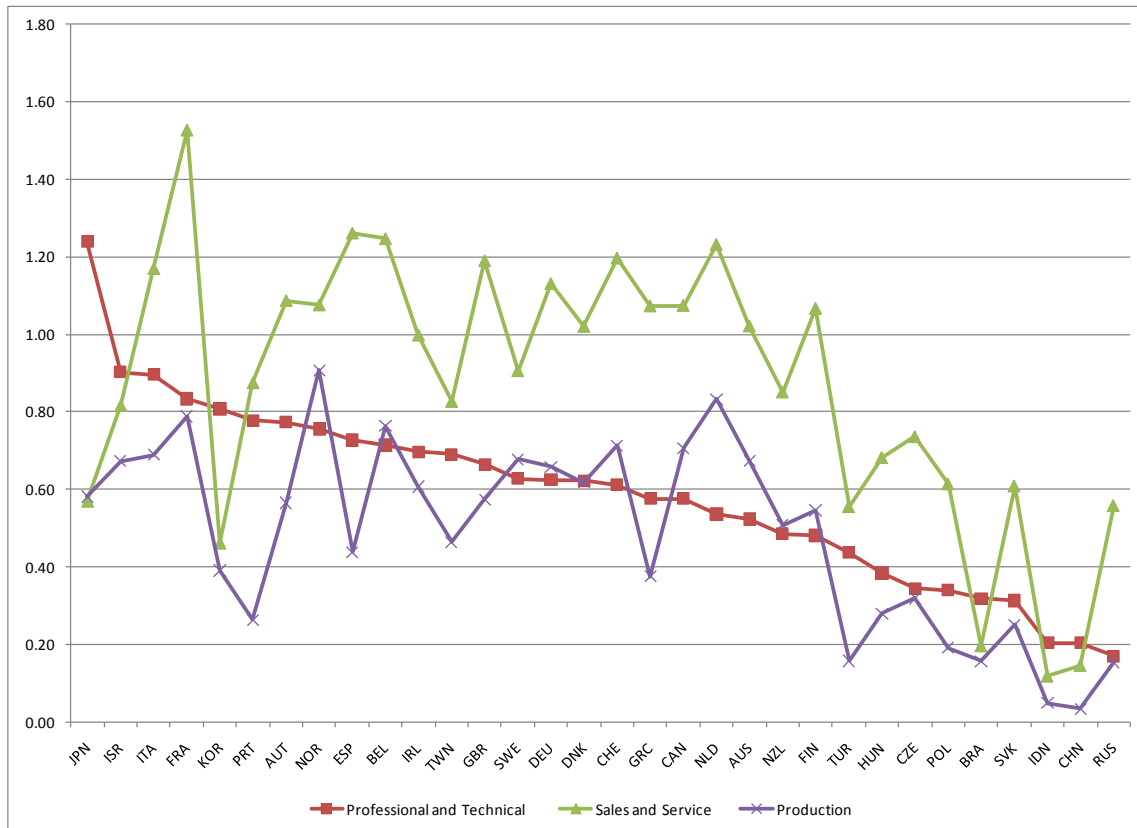


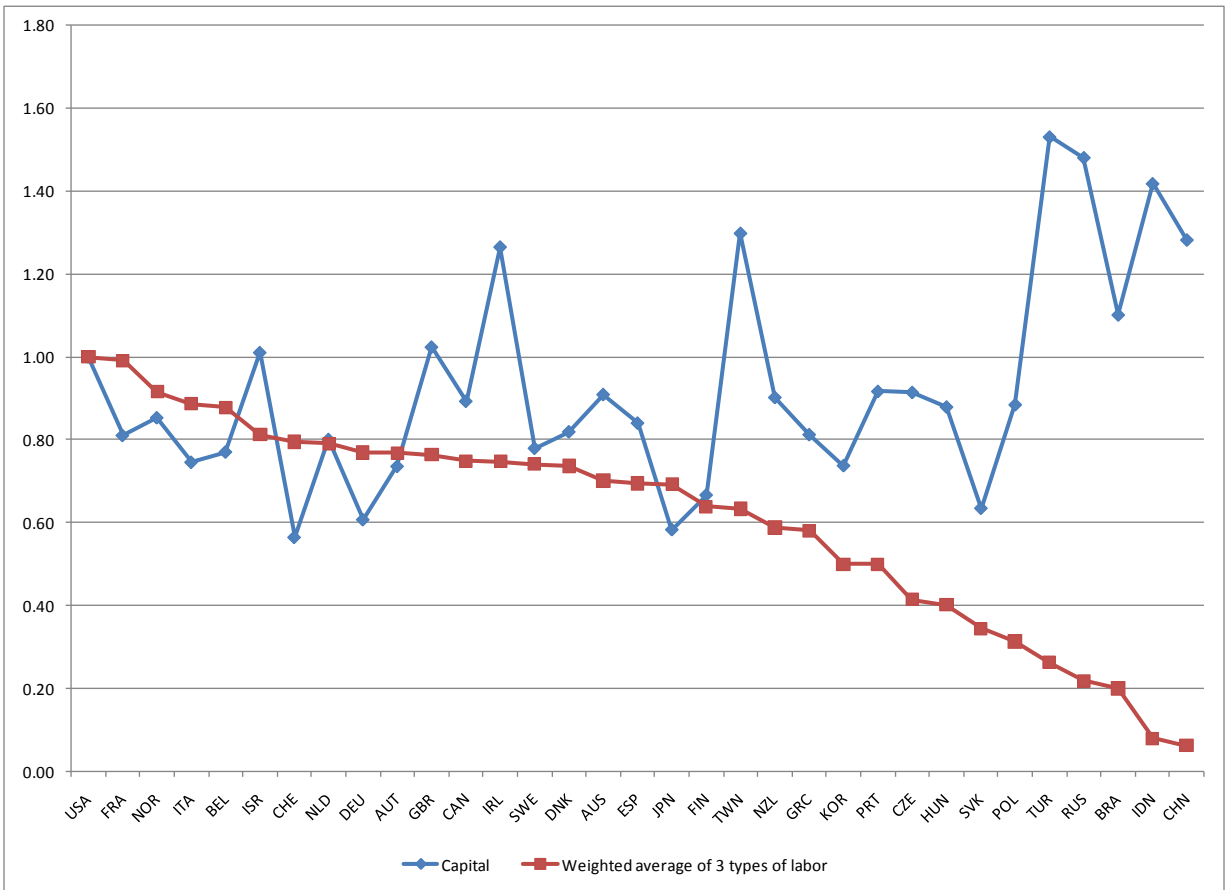
Table 2 presents summary measures for all countries and by high and low wage group. The U.S. in general has higher labor productivity for both professional and technical workers and for production workers when compared to both high and low wage countries. However, for the largest labor group in the U.S., sales and service workers, labor productivity is below the level achieved in 13 of 20 high wage countries. Relative to the U.S., low wage countries have achieved much higher levels of productivity for professional and technical workers than for production workers, who represent the bulk of low wage countries' labor force.

Table 2. Productivity relative to U.S. for three types of labor

	Professional and technical	Sales and Service	Production
Average, 20 high wage countries	0.70	1.06	0.65
Average, 12 low wage countries	0.41	0.55	0.22
Overall Average	0.60	0.87	0.50

The picture is somewhat more surprising when the comparison is between capital productivity and average labor productivity, as presented in Figure 3. Countries with low labor productivity tend to have high capital productivity. The pattern is particularly prominent for the 12 low wage countries in the sample. It is difficult to reconcile this picture with an explanation of productivities inherent in the factors themselves, which suggests that while labor is less productive in these countries, capital is inherently more productive.

Figure 3. Factor-specific productivity for capital and labor



3. Factor productivities and factor payments

The relationship between factor productivities and factor payments depends on the underlying source of differences in factor productivities. Trefler (1993) suggests that productivity differences are inherent in factors and uniform across countries. This implies a clear relationship between the factor specific productivity and factor payments. Under the assumption of zero profits, the vector of output prices p is equal to $A_c^T w_c$, where w_c is the factor payment vector for country c . In the framework of input-output analysis p is by necessity set equal to 1 and quantities are then set to the amount whose price is equal to \$1.² This implies that $A_c^T w_c = A_R^T w_R$, where A_R is the U.S. Leontief matrix and w_R is the U.S. factor payment vector. If $\Pi_c A_c = A_R$, then $A_c^T w_c = A_c^T \Pi_c w_R$, which in turn implies that $w_c = \Pi w$.³ Trefler (1993) substantiates this relationship between factor productivity and factor prices among a large group of developed and developing countries, and Hanson and Slaughter (2002) present evidence for productivity-adjusted factor price equality across 14 U.S. states.

The exact relationship between the productivity estimates and factor payments thus sheds light on the nature of the differences in technology that generate the differences in productivity. If factor specific differences in productivity are uniform across industries, each country's wage relative to the U.S. and each country's rental rate of capital relative to the U.S. should be equal to its respective productivity relative to the U.S. A visual representation of the data for wages and rents is presented in Figure 4. There are clearly significant deviations from this prediction,

² This convention was established by Leontief (1951, p. 72) who noted: "In order to obtain the corresponding physical amounts of all commodities and services, we simply define the unit of physical measurement of every particular type of product so as to make it equal to that amount of the commodity which can be purchased for one dollar at prevailing prices." The implications of this assumption in the international setting are discussed further in Section 4.

³ In the usual case $n > f$ and it is also assumed a factor payment vector that uniquely satisfies the n equations does exist.

particularly for low wage countries. Following Trefler (1993), a more formal test of this hypothesis is that the slope coefficient of a regression of the wage compared to productivity (in natural logarithms) should equal one. An inverse regression is used to account for errors-in variables. For labor, the results of two regressions are

$$\ln(w_{cL}) = 3.66 + 1.17 \ln(\pi_{cL}), R^2 = .94$$

(0.05) (0.054) (1)

$$\ln(\pi_{cL}) = -2.98 + 0.80 \ln(w_{cL}), R^2 = .94$$

(0.11) (0.037) (2)

The interval $[\hat{\beta}^D, 1/\hat{\beta}^R] = [1.18, 1.25]$ gives the probability limits for the true coefficient β . The corresponding regressions for capital are

$$\ln(w_{cK}) = -1.74 + 1.34 \ln(\pi_{cK}), R^2 = .76$$

(0.039) (0.138) (3)

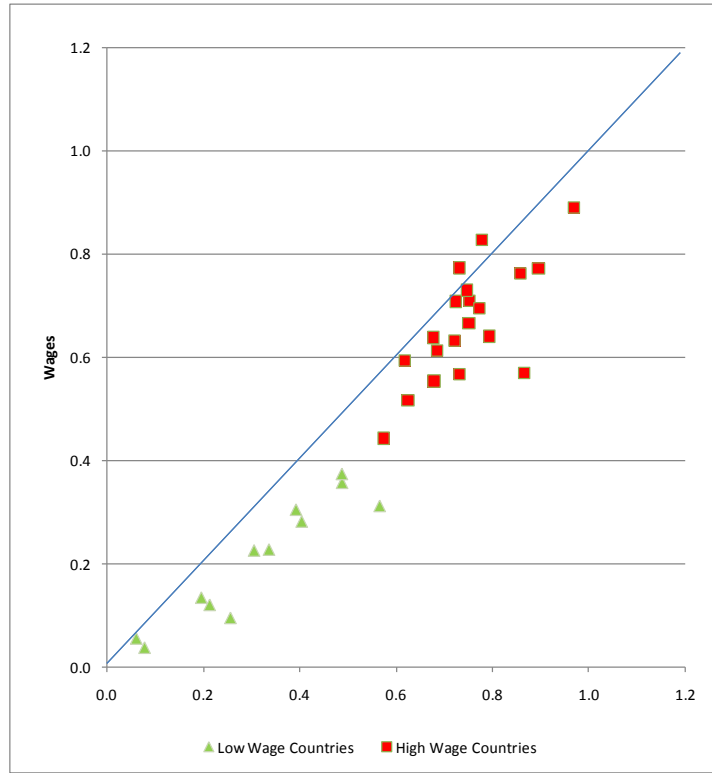
$$\ln(\pi_{cK}) = 0.97 + 0.572 \ln(w_{cK}), R^2 = .76$$

(0.112) (0.058) (4)

where the interval $[\hat{\beta}^D, 1/\hat{\beta}^R] = [1.34, 1.75]$ gives the probability limits for the true coefficient β .

Unlike the results presented in Trefler (1993), this study finds the coefficient for both labor and capital productivities significantly exceeds one. In general, $w_{fc} = \pi_{fc}^{\beta} w_R$, where w_R is the U.S. factor payment and β is greater than one. This confirms what is clearly visible in Figure 3, that low wage countries tend to have low labor productivity relative to the U.S. and even lower wages. However, many low wage countries also have high capital productivity relative to the U.S. and even higher rental rates. Again, this evidence draws into question the assumption that productivity differences are factor-specific and industry-neutral.

(A) Wages and labor productivity



(B) Rental Rates and capital productivity

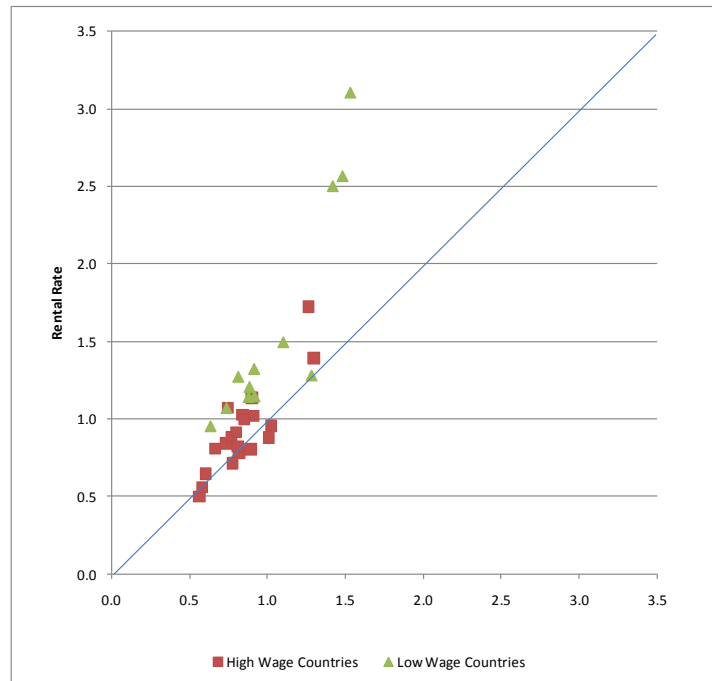


Figure 4. Factor payments and factor-specific productivity

4. An industry-based explanation for factor-specific differences in productivity

The main empirical findings presented thus far suggest two important features of differences in technology across countries: 1) low wage countries tend to use more labor and less capital in a given industry, and 2) when these differences are measured across industries, wages are below and rental rates above the average differences in factor usage, or factor-specific productivity. This section presents a simple theoretical model to account for these differences within the neoclassical framework of constant returns to scale production, and examines the empirical evidence to support this view.

4.1. Uneven Technological Progress

Hall and Jones (1999), Prescott (1998), and Parente and Prescott (2000) establish that total factor productivity (TFP) is the most crucial source of differences in the standard of living between industrial and developing countries. Here I consider the implications of variations in TFP not only in the aggregate between countries, but also between industries, as has been established by Harrigan (1997) and Lai and Zhu (2007), among others. I allow for both differences in TFP and factor-inherent differences in productivity. Consider an internationally standardized factor unit such $\lambda_{fc} a_{fic} = a_{fic}^*$ and $\frac{w_{fc}}{\lambda_{fc}} = w_{fc}^*$. Note that the production function is specified in terms of the standardized international units but only the local units are observed.⁴ Consider a constant elasticity of substitution (CES) unit production function

⁴ A simple illustration is that a single worker may work a different number of hours in different countries. If a “standardized international worker” works 40 hours a week, and in country c workers work on 30 hours a week, so $\lambda_c = .75$. Either a Cobb-Douglas specification of production with variations in TFP or these inherent differences in factor productivity leads to productivity-adjusted factor price equalization.

$$1 = \theta_i \left[\sum_{j=1}^f \alpha_{ji} (a_{ji}^*)^{-b_i} \right] \quad (5)$$

where a_{ji}^* is the unit input requirement of factor j (measured in standardized-international units) in industry i , α_{ji} is the distribution share of factor j in industry i , and θ_i is total factor

productivity in industry i . The elasticity of substitution between factors is given by $\sigma \equiv \frac{1}{1+b}$.

Total factor productivity varies both between countries and between industries within the same country, where the subscript c indicates a specific country. By profit maximization, country c 's unit factor requirement should satisfy

$$a_{fic}^* = p_{ic}^{\sigma_i} \theta_{ic}^{\sigma_i-1} \left(\frac{w_{fc}^*}{\alpha_{fi}} \right)^{-\sigma_i} \quad (6)$$

where w_{fc}^* is the factor f 's payment in country c (in international units) and p_{ic} is the output price of one unit of industry i output.

Henceforth assume that $p_{ic} = 1$ for all industries and all countries. This assumption need not imply that all goods are traded at exogenous world prices. As noted earlier, by construction in input-output data the unit of measure is the amount of inputs necessary to produce one dollar's worth of output. As long as purchasing power parity exchange rates are accurate across industries, these units will also be uniform across industries. A comparison of input output coefficients between two countries c and d in the same industry is then given by

$$\frac{a_{fic}^*}{a_{fid}^*} = \left(\frac{w_{fd}^*}{w_{fc}^*} \right)^{\sigma_i} \left(\frac{\theta_{id}}{\theta_{ic}} \right)^{1-\sigma_i} . \quad (7)$$

Equation (7) shows that differences in factor usage will not be industry-neutral unless the elasticity of substitution between factors is equal to 1, as in the special Cobb-Douglas case. In the following empirical tests I have drawn heavily on the work of Hanson and Slaughter (2002) but I have introduced variations in total factor productivity. If θ_i were the same across countries and industries, international wages would be equal and the right-hand side of the equation would equal 1 even in the more general CES production function. This would in turn imply that

$$\frac{a_{fic}}{a_{fid}} = \frac{\lambda_{fd}}{\lambda_{fc}}$$

among 14 U.S. states.

How can this framework explain the observed pattern of low wages and high rental rates in many low wage countries? An intuitive interpretation based on a simple two industry two factor model can be illustrated by iso-cost lines in a standard general equilibrium setting. Consider a low wage country that has lower total factor productivity in both sectors compared to a high wage country, which means its iso-cost curves will intersect below those of the high-wage country. However, if the “traditional” or labor intensive sector is relatively more backward than the “modern” or capital intensive sector, the rental rate will be above that in the high wage country. The effect is analogous to the famed Stolper-Samuelson effect of a decrease in the price of the labor intensive good, which causes wages to fall and rental rates to increase. This differential effect on factor payments will be greater the lower the elasticity of substitution between factors.

4.2. Empirical evaluation of technology differences

To evaluate these sources of technology differences, I construct a Leontief matrix for each country and compare the input output coefficients industry by industry. Since labor by occupational category is only available at the fourteen industry aggregation for thirty countries in the sample I also aggregate the OECD input output data into fourteen conforming industries. For empirical estimation, equation (7) requires industry specific measures of TFP and economy wide- measures of factor payments for each country. The rental rate is inferred from value-added payments to capital given a measure of each country's total capital stock. This economy-wide rate of return is used in turn to infer the stock of capital used in each industry. Measures of TFP and wages are estimated from the direct and indirect unit input-output coefficients in the following manner.

Consider the vector of the value-added payment to labor per PPP dollar of output, ϖ , which is computed from the input-output data. Economy wide wage estimates for each country are given by an OLS estimate of $\varpi = w_1 a_1 + w_2 a_2 + \varepsilon$, where w_f is the estimated wage, a_f is the corresponding row vector of the country's technology matrix A , and ε is an error term. Due to the limited number of observations for each country, labor was aggregated into two types: more skilled (professional and technical) and less skilled (all others). The results of this simple regression for each country are generally statistically significant even given the small sample size, and accord with the prior expectation that skilled labor should receive a higher wage.

A widely used index of TFP (e.g. Harrigan, 1997, and Lai and Zhu, 2007) based on Caves et al (1982) is used to compute TFP in each industry. The index is derived from the flexible translog functional form and so does not assume that factor payment shares are constant.

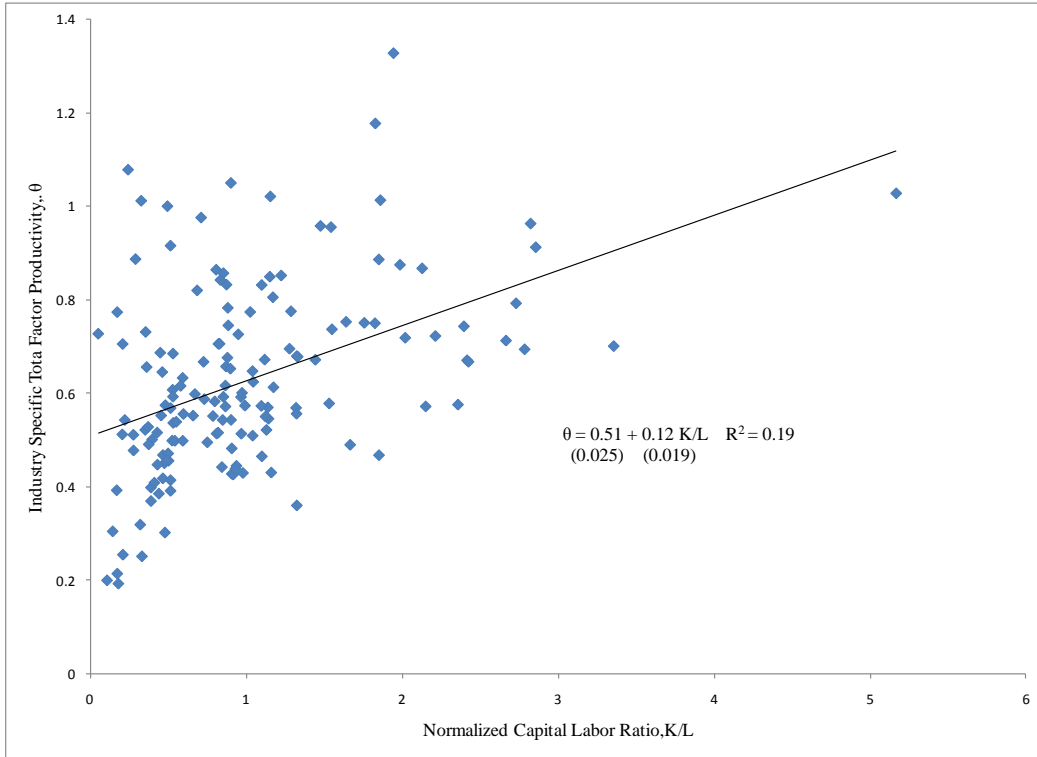
The TFP index is constructed from factor payment shares and factor inputs for each industry, which can be readily constructed from the input output coefficients and factor payments data used in this study. The results of these computations for high wage and low wage country averages are presented in Table 5.

Industry Total Factor Productivity Index Relative to the U.S.					
ISIC Rev. 3 Code	Description	19 High wage Countries		11 Low wage Countries	
		Average	Std. Dev.	Average	Std. Dev.
A,B	Agriculture and Fishing	0.69	0.16	0.62	0.14
C	Mining	0.75	0.14	0.74	0.22
D	Manufacturing	0.74	0.12	0.58	0.11
E	Electricity, gas and water supply	0.83	0.14	0.86	0.21
F	Construction	0.77	0.12	0.59	0.12
G	Wholesale and retail trade	0.70	0.11	0.55	0.13
H	Hotels and restaurants	0.86	0.13	0.67	0.14
I	Transport and communications	0.74	0.12	0.63	0.17
J	Financial intermediation	0.74	0.11	0.63	0.16
K	Real estate	0.75	0.12	0.74	0.15
L	Public administration	0.95	0.21	0.65	0.24
M	Education	0.98	0.17	0.55	0.26
N	Health and Social work	0.79	0.15	0.57	0.20
O,P,Q	Other	0.57	0.13	0.37	0.11
	All Industries	0.78	0.17	0.63	0.20

These computations confirm a wide range of TFP within these broad industry groups. This is particularly notable for developing countries, whose TFP may even exceed that in the U.S. in some modern sectors such as electricity, but varies widely between the differing sectors. If differences in TFP explain the pattern of factor payments seen in Figure 4, capital intensive industries should have higher TFP. This pattern is substantiated for the set of 11 low wage

countries by a simple regression of TFP against the capital labor ratio in each industry (Figure 5).

Figure 5. Uneven Technological progress in 11 low wage countries



Given estimates of TFP by industry and economy-wide factor payments, equation (7) suggests a framework for estimating the industry-specific CES elasticity of substitution σ_i for each industry. In the first test I will assume that all differences in factor usage stem from differences in total factor productivity so that it is not necessary to express local units in a standardized international form. This gives

$$\ln(a_{fic}) = \beta_0 + \beta_1 \ln(a_{fid}) + \beta_2 \ln\left(\frac{w_{fd}}{w_{fc}}\right) + \beta_3 \ln\left(\frac{\theta_{id}}{\theta_{ic}}\right) + \varepsilon_{ficd} . \quad (8)$$

Since this is a pair-wise comparison of input-output coefficients for each industry, given the sample of thirty countries there are 435 unique pairs and 3 factors for a total sample of 1305 observations per industry. A seemingly unrelated regression across all 14 industries also permits improved estimation results due to country pair-specific correlation in the error term across industries. The results of this estimation are presented in Table 6. The general magnitude and signs of all the estimated coefficients accord with the CES specification in equation (7). The point estimate of σ_i given by $\hat{\beta}_2$ is significantly less than 1 in all fourteen industries. However, the more precise restriction that $\hat{\beta}_3 = 1 - \hat{\beta}_2$ is rejected in every industry.

A possible source of misspecification is that there are also differences in factor-specific productivity so that equation (7) expressed in local units becomes

$$\frac{a_{fic}}{a_{fid}} = \left(\frac{\lambda_{fd}}{\lambda_{fc}} \right)^{1-\sigma_i} \left(\frac{w_{fd}}{w_{fc}} \right)^{\sigma_i} \left(\frac{\theta_{id}}{\theta_{ic}} \right)^{1-\sigma_i}. \quad (9)$$

Since the values of λ cannot be observed but they vary in the same fashion (by factor and country pair) as the wage ratio, equation (9) can be tested by a fixed effects model similar to that used in Hanson and Slaughter:

$$\ln(a_{fic}) = \alpha_{fcd} + \beta_1 \ln(a_{fid}) + \beta_2 \ln \left(\frac{\theta_{id}}{\theta_{ic}} \right) + \varepsilon_{fcd} \quad (10)$$

where α_{fcd} is a fixed effect for each factor country pair which captures the unobservable international wage differences. Here the elasticity of substitution is assumed to be the same in every industry so that $\beta_2 = 1 - \sigma$. The results of this specification are also presented in Table 6.

Again the estimate of the elasticity of substitution is significant and less than one, although one can reject the hypothesis that $\beta_1 = 1$.

Table 6. Results of two CES specifications for industry-specific TFP

Estimation of Equation (8) with Seemingly Unrelated Regression across 14 Industries				
Industry	β_0	β_1	β_2	β_3
Agriculture and Fishing	-0.21	0.96	0.77	0.53
<i>standard error</i>	<i>0.025</i>	<i>0.003</i>	<i>0.019</i>	<i>0.029</i>
Mining	-0.13	0.99	0.57	0.91
<i>standard error</i>	<i>0.039</i>	<i>0.005</i>	<i>0.029</i>	<i>0.054</i>
Manufacturing	-0.09	0.98	0.51	0.73
<i>standard error</i>	<i>0.016</i>	<i>0.002</i>	<i>0.012</i>	<i>0.020</i>
Electricity, gas and water supply	-0.10	0.99	0.58	0.77
<i>standard error</i>	<i>0.020</i>	<i>0.002</i>	<i>0.015</i>	<i>0.029</i>
Construction	-0.07	0.98	0.43	0.75
<i>standard error</i>	<i>0.014</i>	<i>0.002</i>	<i>0.010</i>	<i>0.019</i>
Wholesale and retail trade	-0.10	0.97	0.42	1.01
<i>standard error</i>	<i>0.018</i>	<i>0.002</i>	<i>0.013</i>	<i>0.027</i>
Hotels and restaurants	-0.10	0.97	0.47	1.00
<i>standard error</i>	<i>0.022</i>	<i>0.003</i>	<i>0.016</i>	<i>0.033</i>
Transport and communications	-0.08	0.98	0.54	0.92
<i>standard error</i>	<i>0.016</i>	<i>0.002</i>	<i>0.012</i>	<i>0.019</i>
Financial intermediation	-0.04	0.99	0.59	0.64
<i>standard error</i>	<i>0.027</i>	<i>0.003</i>	<i>0.020</i>	<i>0.044</i>
Real estate	-0.11	0.98	0.59	0.58
<i>standard error</i>	<i>0.019</i>	<i>0.002</i>	<i>0.014</i>	<i>0.034</i>
Public administration	-1.10	0.86	0.88	0.10
<i>standard error</i>	<i>0.038</i>	<i>0.004</i>	<i>0.028</i>	<i>0.038</i>
Education	0.07	1.00	0.38	0.74
<i>standard error</i>	<i>0.023</i>	<i>0.003</i>	<i>0.016</i>	<i>0.024</i>
Health and Social work	0.00	0.99	0.48	0.68
<i>standard error</i>	<i>0.020</i>	<i>0.002</i>	<i>0.015</i>	<i>0.026</i>
Other	-0.05	0.98	0.70	0.69
<i>standard error</i>	<i>0.022</i>	<i>0.003</i>	<i>0.016</i>	<i>0.028</i>

Estimation of Equation 10 with fixed effects for factor country pairs

	β_1	β_2
	0.70	0.56
<i>standard error</i>	<i>0.004</i>	<i>0.009</i>
No obs.	18,096	
R-squared	0.99	

The empirical evidence presented here for a uniform CES industry specification with all variations across countries due to differences in TFP is suggestive but not conclusive. However, when taken together with the evidence presented in Section 3 that factor price differences are not fully explained by economy-wide differences in productivity, it seems reasonable to conclude that industry specific variations in TFP combined with less than unit elasticity of substitution between factors play a major role in explaining variations in wages and rents across countries.

5. Conclusion

As more data on the technology of different countries at an industry level becomes available, it is apparent that all variations in this technology cannot be modelled captured by simple factor-augmenting differences in productivity. This in turn suggests that productivity-adjusted factor price equalization does not fully explain persistent and large differences in factor prices. A comparison of factor usage across industries does confirm that low wage countries have low labor productivity across all skill types of labor, but also surprisingly reveals that capital may be highly productive in the same environments. This seeming paradox can be explained by recognizing that large differences in total factor productivity long established in the aggregate are the source of differences in factor usage across industries, and that capital-intensive sectors appear to modernize more rapidly in low wage countries. Neither of these assumptions seem implausible. However, the evidence for this view is not conclusive. Either differences in technology are even more idiosyncratic than the simple CES specification presented here, or the data are too poor to test the technology specification (or both).

Data Appendix

Labor data by occupational and industry is taken from the International Labor Organization on-line data source Laborsta Table 1.E. This was used for both total endowments and labor by industry. U.S. labor data is taken from the Occupational Employment Survey for the year 2000. Since these two labor data sources use a different typology, a concordance was developed (given below) to aggregate both into the three broad categories used in this study. For the U.S., ILO Table 1.E. was also used to adjust employment in the agriculture and construction sector. This assured that the total labor in the U.S. from the OES – which excludes self-employed labor – was equal to the total labor in given in Table 1.E. OES data is categorized by SIC and a concordance published by the United Nations was used to match the SIC to the OECD input output categories based on ISIC version 3.

Data on the capital stock was constructed from Penn World Tables 6.2 data in the following manner. Starting with the measure of total production from the OECD input-output data in 2000, output in prior years (as far back as data allowed) was inferred from the growth rate of output published in PWT. Investment in each year was then inferred from the investment share of GDP series in PWT. The initial capital stock in the earliest year (1951 for most countries) was determined by $\frac{I_t}{g + \delta}$ where I_t is investment in initial year, g is the average rate of growth of GDP for next 5 years, and δ is the depreciation rate assumed to be 0.04. If data in PWT did not go back as far as 1951 a similar method was used with the earliest available year. For Russia, data was only available from 1991 and for Slovakia only from 1988 so the capital stock for these countries is less accurate.

Concordance between U.S. Occupation Codes and International Occupational Codes

Standard Occupational Classification Descriptions	ISOC-88	Type
11-0000 Management occupations	Major Group 1 Legislators, senior officials and managers	1
13-0000 Business and financial operations occupations	Major Group 1 Legislators, senior officials and managers	1
15-0000 Computer and mathematical occupations	Major Group 2 Professionals	1
17-0000 Architecture and engineering occupations	Major Group 2 Professionals	1
19-0000 Life, physical, and social science occupations	Major Group 2 Professionals	1
23-0000 Legal occupations	Major Group 2 Professionals	1
25-0000 Education, training, and library occupations	Major Group 2 Professionals	1
29-0000 Healthcare practitioners and technical occupations	Major Group 2 Professionals	1
21-0000 Community and social services occupations	Major Group 3 Technicians and associate professionals	1
27-0000 Arts, design, entertainment, sports, and media occupations	Major Group 3 Technicians and associate professionals	1
49-0000 Installation, maintenance, and repair occupations	Major Group 3 Technicians and associate professionals	1
43-0000 Office and administrative support occupations	Major Group 4 Clerks	2
31-0000 Healthcare support occupations	Major Group 5 Service workers and shop and market sales workers	2
33-0000 Protective service occupations	Major Group 5 Service workers and shop and market sales workers	2
35-0000 Food preparation and serving related occupations	Major Group 5 Service workers and shop and market sales workers	2
39-0000 Personal care and service occupations	Major Group 5 Service workers and shop and market sales workers	2
41-0000 Sales and related occupations	Major Group 5 Service workers and shop and market sales workers	2
45-0000 Farming, fishing, and forestry occupations	Major Group 6 Skilled agricultural and fishery workers	3
47-0000 Construction and extraction occupations	Major Group 7 Craft and related trade workers	3
53-0000 Transportation and material moving occupations	Major Group 8 Plant and machine operators and assemblers	3
37-0000 Building and grounds cleaning and maintenance occupations	Major Group 9 Elementary occupations	3
51-0000 Production occupations	Major Group 8 Plant and machine operators and assemblers	3

1: Professional and Technical; 2: Sales and Services; 3: Production

Appendix Table 1

Country	Code	Capital Stock (\$ millions)	Professional and Technical			Production Workers (1000)	Total workers (1000)	Average Wage (\$ 1000)	Average Rental Rate
			Workers (1000)	Service Workers (1000)	Workers (1000)				
Australia	AUS	1,369,662	3,545	2,369	2,717	8,631	27.6	0.14	
Austria	AUT	685,248	1,188	1,107	1,610	3,905	30.0	0.12	
Belgium	BEL	808,435	1,683	1,093	1,308	4,084	34.3	0.12	
Brazil	BRA	2,604,063	13,299	27,882	32,961	74,142	6.0	0.21	
Canada	CAN	2,622,727	5,979	4,335	5,132	15,445	34.7	0.11	
Switzerland	CHE	1,010,690	1,663	1,046	1,195	3,904	37.2	0.07	
China	CHN	5,833,356	53,140	88,475	578,758	720,373	2.5	0.18	
Czech Republic	CZE	389,464	1,736	1,047	2,288	5,071	12.7	0.18	
Germany	DEU	8,222,419	14,056	8,861	13,068	35,985	31.9	0.09	
Denmark	DNK	459,915	1,132	749	933	2,814	28.4	0.11	
Spain	ESP	2,310,112	4,660	4,127	8,117	16,904	24.9	0.14	
Finland	FIN	429,910	1,081	514	903	2,498	23.2	0.11	
France	FRA	4,716,165	7,997	5,123	7,767	20,887	40.0	0.12	
United Kingdom	GBR	3,707,701	10,420	7,349	9,950	27,718	32.8	0.13	
Greece	GRC	530,768	1,186	1,017	1,948	4,151	14.0	0.18	
Hungary	HUN	309,576	1,225	846	1,778	3,849	13.7	0.16	
Indonesia	IDN	934,419	8,328	21,249	60,205	89,781	1.7	0.35	
Ireland	IRL	178,507	482	396	605	1,483	25.5	0.24	
Israel	ISR	269,677	585	653	695	1,933	28.9	0.12	
Italy	ITA	4,267,704	6,258	6,251	8,665	21,174	25.6	0.15	
Japan	JPN	13,788,377	11,175	29,431	23,475	64,081	28.7	0.08	
Korea, Rep.	KOR	2,382,182	3,881	7,916	9,261	21,058	16.1	0.15	
Netherlands	NLD	1,344,733	3,583	1,875	2,042	7,500	31.2	0.13	
Norway	NOR	557,779	946	678	654	2,278	34.7	0.14	
New Zealand	NZL	224,794	616	469	603	1,688	19.9	0.16	
Poland	POL	1,010,194	4,484	3,149	8,706	16,339	10.2	0.17	
Portugal	PRT	394,076	929	1,047	2,710	4,687	16.8	0.16	
Russian Federation	RUS	1,787,197	22,619	9,778	32,211	64,608	5.4	0.36	
Slovak Republic	SVK	215,492	759	500	1,167	2,426	10.2	0.13	
Sweden	SWE	688,186	1,724	1,194	1,220	4,138	31.8	0.10	
Turkey	TUR	649,089	1,991	4,986	13,898	20,875	4.5	0.43	
Taiwan	TWN	823,439	2,636	2,770	3,976	9,382	26.7	0.20	
United States	USA	25,896,635	45,277	52,048	37,386	134,711	45.9	0.14	

References

- Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert. 1982. "Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers." *The Economic Journal*, 92:365, pp. 73-86.
- Dollar, David and Edward N. Wolff. 1993. "Competitiveness, convergence, and international specialization ". MIT Press: Cambridge MA.
- Fisher, Eric O'N and Kathryn G. Marshall. 2008. "The factor content of trade when countries have different technologies." *unpublished manuscript*.
- Hall, Robert and Charles Jones. 1999. "Why Do Some Countries Produce So much more output per worker than others?" *Quarterly Journal of Economics*, pp. 83-116.
- Hanson, Gordon H. and Matthew J. Slaughter. 2002. "Labor-Market Adjustment in Open Economies: Evidence from US States." *Journal of International Economics*, 57:1, pp. 3-29.
- Harrigan, James. 1997. "Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model." *American Economic Review*, 87:4, pp. 475-94.
- Lai, Huwen and Susan Chun Zhu. 2007. "Technology, endowments, and the factor content of bilateral trade." *Journal of International Economics*, 71, pp. 389-401.
- Maskus, Keith and Shuichiro Nishioka. 2008. "Development-Related Biases in Factor Productivities and the HOV Model of Trade." CESifo Working Paper No. 2253
- Maskus, Keith E. and Allan Webster. 1999. "Estimating the HOV Model with Technology Differences Using Disaggregated Labor Skills for the United States and the United Kingdom." *Review of International Economics*, 7:1, pp. 8-19.
- Parente, Stephen L. and Edward C. Prescott. 2000. *Barriers to Riches*: MIT Press.
- Prescott, Edward C. 1998. "Needed: A Theory of Total Factor Productivity." *International Economic Review*, 39:3, pp. 525-51.
- Trefler, Daniel. 1993. "International Factor Price Differences: Leontief was Right." *Journal of Political Economy*, 101:6, pp. 961-87.
- Trefler, Daniel. 1995. "The Case of the Missing Trade and Other Mysteries." *American Economic Review*, 85:5, pp. 1029-46.
- Woodland, A. D. 1982. *International trade and resource allocation*. Amsterdam: North-Holland.