International Productivity and Factor Price Comparisons

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January 2010

Abstract: Using OECD input-output tables for a diverse group of 33 countries in the year 2000, I attempt to replicate Trefler (1993)'s findings that substantiated productivity-adjusted factor price equalization. I compute factor payments for aggregate labor and capital using value-added data adjusted for self-employment *by sector*, a correction which differs notably for low income countries from a widely-used economy-wide self-employment correction. I find a distinctive bias in the relationship between factor productivity and factor prices depending on whether a country has a high or low wage rental ratio compared to the United States. I explain this bias by industry-based differences in production technology together with less than unitary elasticity of substitution between factors.

JEL CLASSIFICATION: F16, J24, J31, O15

I. Introduction

There remains a wide dispersion in factor payments across countries even after the steady expansion of international trade as a share of world GDP during the last several decades. Within a large and diverse sample of open economies in the year 2000, average wages vary by a factor of twenty-fold and the rate of return to capital varies by almost four-fold.[1] In the context of the neoclassical general equilibrium model of international trade, this apparent failure of factor price equalization (FPE) can be attributed to differences in productivity, so that productivity-adjusted FPE may still hold. In this paper I revisit Trefler's (1993) influential study that substantiated productivity-adjusted FPE among a group of 33 countries using data from 1983.[2] Rather than imputing the productivity parameters from international trade data as Trefler did, I measure them directly from data on country endowments and production by sector, together with a detailed technology matrix for the United States. I show that factor-specific measures of productivity are strongly correlated with the pattern of wages and rental rates but do not support a strict interpretation of productivity–adjusted FPE. My results also differ from Trefler in that I do not find evidence of a positive correlation between the factor-specific productivity of capital and

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[1] The sample includes 33 industrial and developing economies that together account for 78% of world GDP in 2005 based on World Bank (2008) purchasing power parity measures. Measuring openness by the trade ratio, (exports + imports)/GDP, the country with the lowest trade ratio (0.22) in the sample is the United States, and the median value is 0.72.

[2] Let a_{fid} measure the direct and indirect input of factor f needed to produce one unit of industry i's output in country d. When compared to a reference country c, $\pi_{fid} = a_{fic}/a_{fid}$, where π_{fid} is the factor–specific productivity measure for industry i. Factor-specific productivity is usually assumed to be the same across industries, denoted by π_{fd}, and productivity-adjusted FPE implies that $w_{fd} = \pi_{fd} w_{fc}$ where w_{fd} is the payment to factor f in country d.

labor. In fact, many low income countries with low labor productivity also have relatively high capital productivity.[3]

To explain these findings I appeal to the extensive literature on variations in total factor productivity (TFP) among countries at different levels of economic development, well-documented at both a national and industry level (see Hall and Jones, 1999; Acemoglu and Zilibotti, 2001; Yeaple and Golub, 2007). If technological progress is uneven in the sense that some industries have relatively higher TFP than others when compared to a reference country, the factors employed intensively in the more advanced sectors will have a higher rate of return and economy-wide usage of these factors will be correspondingly lower. The notion that factor-specific productivity is inherent in the factor itself is misleading since differences in factor usage stem from an underlying process of industrialization wherein some sectors modernize more quickly. The rate of diffusion of modern technology and efficiency can vary across sectors for a variety of reasons, and the evidence for uneven development is especially strong when contrasting the agricultural sector to the rest of the economy. Many of today's low income countries continue to employ a large share of their labor force in relatively backward labor-intensive agricultural production in spite of rapid growth in urban manufacturing.[4]

I propose a simple theoretical framework with two sectors – traditional agriculture and modern manufacturing - and two factors – aggregate labor and capital - to show how measured factor-specific differences in productivity can stem from sector - specific differences in production technology. When the production technology is Cobb-Douglas with only sector-

[3] Maskus and Nishioka (2009) find a similar development bias in their measures of factor productivities.

[4] Timmer (2007) details the special problems facing the agricultural sectors of late-comers to industrialization which impede the process of structural transformation. Gollin et al. (2004) show that the relative output per worker in agriculture compared to non-agriculture production among late-comers is not only low, it is significantly lower than that experienced during the past structural transformation of today's industrial nations.

specific Hicks neutral productivity variations, differences in the technology matrix reflect different relative factor payments (assuming exogenous world prices). A country with high average wages does not necessarily have more industrious workers, but by profit-maximization it will employ less labor in both sectors relative to a low wage country. Uneven technological progress can still explain why capital is more productive than labor, but otherwise the sector-specific differences in technology will generate uniform factor-specific differences in productivity. If, on the other hand, the sector-specific production technology is modeled with a constant elasticity of substitution (CES) production function and the elasticity of substitution between capital and labor is less than one, differences in the countries' technology matrices will be more complex and factor-specific productivities will not be uniform across sectors.

Empirically, I find that when factor-specific productivity differences are averaged across sector they are tightly correlated with factor payments, but there is a specific estimation bias. In particular, countries with low wage rental ratios have lower wages and higher rental rates than would be predicted by their factor-specific productivity relative to the United States, and the reverse is true for countries with high wage rental ratios. This pattern can be explained by less than unitary substitution between factors together with variations in TFP across sector.

In the international trade literature, the standard explanations for variations in wage rental ratios include the existence of cones of diversification (see Debaere and Demiroglu, 2003; Schott, 2003) and the existence of non-traded goods. At the 47-sector level of aggregation used in this study, OECD input-output data show production occurs in almost all sectors among all countries in this sample so different cones of diversification cannot be distinguished. It is also problematic to separate the influence of non-traded goods from TFP, since mathematically they enter the production function in the same fashion (see Harrigan, 1997). In the absence of detailed international price indexes by sector, I rely on the World Bank International Comparison Project (2008) purchasing power parity exchange rates to measure real output in all sectors. However, I document differences in TFP between two major sectors, agriculture and manufacturing, that are typically considered traded goods sectors, and show that the pattern of measured TFP across fourteen broad sectors fits the hypothesis that countries with low wage rental ratios tend to have higher TFP in relatively capital intensive sectors.

The measurement of detailed technology matrices for international comparisons is often limited by data availability. The OECD now publishes extensive input-output data for OECD and many non-OECD countries that is the foundation of this study. The input-output tables report value-added payments for gross operating surplus, compensation of employees, and indirect taxes at the 2-digit ISIC level of aggregation, but conforming data on labor employment and capital usage is limited. Instead of constructing individual country technology matrices, I construct a single technology matrix for the United States and measure the amount of capital and labor the United States would employ to produce other countries' output (measured by sector). I then compare these "virtual endowments" to the countries' actual endowments to infer factor-specific productivity. This approach has the advantage of weighing industry-specific differences in factor usage by their importance in the overall output in a given country, and of limiting the errors in technology measurement to the U.S. only.

To measure factor payments I simply divide the labor share of value-added by the total number of workers employed, and the capital share by the total stock of capital. I incorporate the findings of Gollin (2002) that the share of employee compensation in value-added is a biased measure of the labor share since low income countries have more self-employed workers whose labor income is not included in employee compensation. A standard correction for this measurement problem emphasized by Bernanke and Gurkaynak (2001) that uses the aggregate share of self-employment in fact overstates the labor share of income since the self-employed are concentrated in sectors such as agriculture with low value-added per worker. I construct a more accurate adjustment that uses value-added and self-employment by fourteen broad sectors.

I also examine the strong assumption of Caselli and Feyrer (2007) that over fifty percent of non-labor value-added payments in low income countries represent payments to natural resource stocks that are not included in the standard measure of the produced capital stock. Using disaggregated value-added payments to natural resource-intensive sectors, I find that their suggested correction based on World Bank (2006) imputations of natural capital appears to greatly exaggerate the measured natural resource component of value-added. There are many possible explanations for this discrepancy since the World Bank study casts a very wide net over the natural wealth of a nation - including potentially non-earning assets such as protected areas. I estimate produced capital using local prices to account for international differences in the cost of capital as suggested by Caselli and Feyrer, but in the absence of a more accurate correction for natural resource payments I assume that all earnings not paid to labor or indirect taxes are returns to this produced capital stock.

The rest of the paper is organized as follows: in Section II I present the details of these adjustments to value-added and the resulting factor payment measures. In Section III I present the factor-specific measures of productivity and compare them to the computed factor payments. In Section IV I present a framework of uneven technological progress and some empirical support for this view, followed by a brief concluding section.

II. Measuring factor payments

The crucial ingredients for this study are data on endowments for a diverse sample of countries, data on factor payments in those countries, a detailed technology matrix that describes factor usage by sector in the reference country, and conforming output by sector for other countries in the sample.   To maintain a high degree of uniformity between these different measures, I use OECD input-output tables for 33 countries in or near the year 2000 for both output by sector and value-added payments by sector, including gross operating surplus (GOS), compensation of employees, and indirect taxes on production. I focus on only two factors: aggregate labor, measured by the number of employed workers, and the total capital stock, measured in a manner described below. I first consider several possible adjustments to the raw value-added data that take into account differences in self-employment and natural resources especially relevant for countries at different stages of economic development.

The correct measure of labor's share of value-added is explored in depth by Gollin (2002) using aggregate national accounts data. Gollin emphasizes that low income countries have a disparately large number of self-employed workers and proprietors whose income is recorded as part of gross operating surplus, whereas compensation of employees includes only the wage and non-wage compensation of employees. Some countries do collect data on this special category of mixed income, defined as the operating surplus of unincorporated enterprises, but many countries do not provide this data even at the aggregate national income level. Without any correction for the misallocation of labor income, many developing countries have an inordinately low labor share of labor income when measured by employee compensation, which would of course bias the estimate of average wages used here.

Gollin explores several different corrections to this bias, but Bernanke and Gurkaynak (2001) emphasize a particularly useful way to address the problem without the aid of aggregate national income data on mixed income. They use self-employment data to estimate mixed income, MI, according to the simple formula MI= *se*(GDP – indirect taxes), where *se* is the share of self-employed workers in the total labor force. Given this imputed mixed income, they assume the labor share of income is the same in both the corporate and unincorporated sectors, and therefore is given by

$$Labor\ share = \frac{corporate\ employee\ compensation}{GDP - indirect\ taxes - mixed\ income} \quad (1)$$

Bernanke and Gurkaynak note that in countries with a very high share of self-employment, the resulting labor share is very high and may even exceed one. Although they attribute this to unreliable data, another important factor is the concentration of the self-employed in low value-added sectors such as agriculture. Because the OECD input-output data compiles value-added data by sector and self-employment data is provided by the ILO at a broad industry level, I am able to use the self-employment correction to compute mixed income by broad sector. Table 1 presents the results of three estimates of labor share, including the naïve estimate based on the share of employee compensation only, the adjustment based on only the overall level of self-employment, and the adjustment based on self-employment by sector. In low income countries such as Indonesia and Brazil, the difference in the two self-employment adjustments is substantial, although in most countries the difference is more moderate. When low value-added sectors are taken into consideration, there remains a positive correlation between GDP per worker and labor share, illustrated in Figure 1. The aggregate national income account data appears to conceal some variations at the industry level that restore this controversial correlation.

TABLE 1
Alternative estimates of labor's share of value-added less indirect taxes

Country	Year	Abbreviation	GDP per worker, PPP $s	Employee compensation share	Labor share with mixed income estimted by aggregate self-employment	Labor share with mixed income estimated by self-employment by sector
Australia	1998/99	AUS	50,570	0.55	0.66	0.66
Austria	2000	AUT	52,890	0.59	0.68	0.64
Belgium	2000	BEL	60,241	0.58	0.69	0.69
Brazil	2000	BRA	14,614	0.45	0.73	0.58
Canada	2000	CAN	54,732	0.64	0.76	0.73
China	2000	CHN	3,939	0.63	-	-
Czech Republic	2000	CZE	27,856	0.47	0.57	0.57
Denmark	2000	DNK	51,457	0.61	0.67	0.66
Finland	2000	FIN	44,236	0.54	0.62	0.61
France	2000	FRA	67,402	0.61	0.68	0.67
Germany	2000	DEU	54,331	0.61	0.68	0.67
Greece	1999	GRC	38,445	0.38	0.62	0.54
Hungary	2000	HUN	27,671	0.52	0.60	0.60
Indonesia	2000	IDN	5,411	0.32	0.96	0.64
Ireland	1998	IRL	53,669	0.47	0.58	0.55
Israel	1995	ISR	53,177	0.63	0.73	0.70
Italy	2000	ITA	60,752	0.46	0.63	0.62
Japan	2000	JPN	48,453	0.63	0.76	0.70
Korea	2000	KOR	33,721	0.49	0.78	0.64
Netherlands	2000	NLD	55,419	0.58	0.65	0.64
New Zealand	1995/96	NZL	36,787	0.48	0.61	0.61
Norway	2001	NOR	70,403	0.50	0.54	0.54
Poland	2000	POL	21,427	0.49	0.66	0.57
Portugal	1999	PRT	31,405	0.56	0.75	0.68
Russia	2000	RUS	15,835	0.35	0.38	0.37
Slovak Republic	2000	SVK	23,051	0.46	0.51	0.51
Spain	2000	ESP	46,960	0.56	0.69	0.66
Sweden	2000	SWE	50,611	0.66	0.73	0.71
Switzerland	2001	CHE	65,543	0.67	-	-
Taiwan	2001	TWN	46,269	0.61	-	-
Turkey	1998	TUR	17,917	0.25	0.57	0.44
United Kingdom	2000	GBR	49,519	0.65	0.73	0.72
USA	2000	USA	70,679	0.63	0.68	0.68
Correlation with GDP per worker				0.59	0.02	0.53

Source. GDP per worker in PPP$ are in base year 2000, based on OECD input-output tables, World Bank (2008) purchasing power parity exchange rates, and total employment from ILO LABORSTA Table 1.E. Labor shares are my computations using self-employment by sector from ILO LABORSTA Table 1.C. China, Switzerland and Taiwan do not report self-employment by sector.

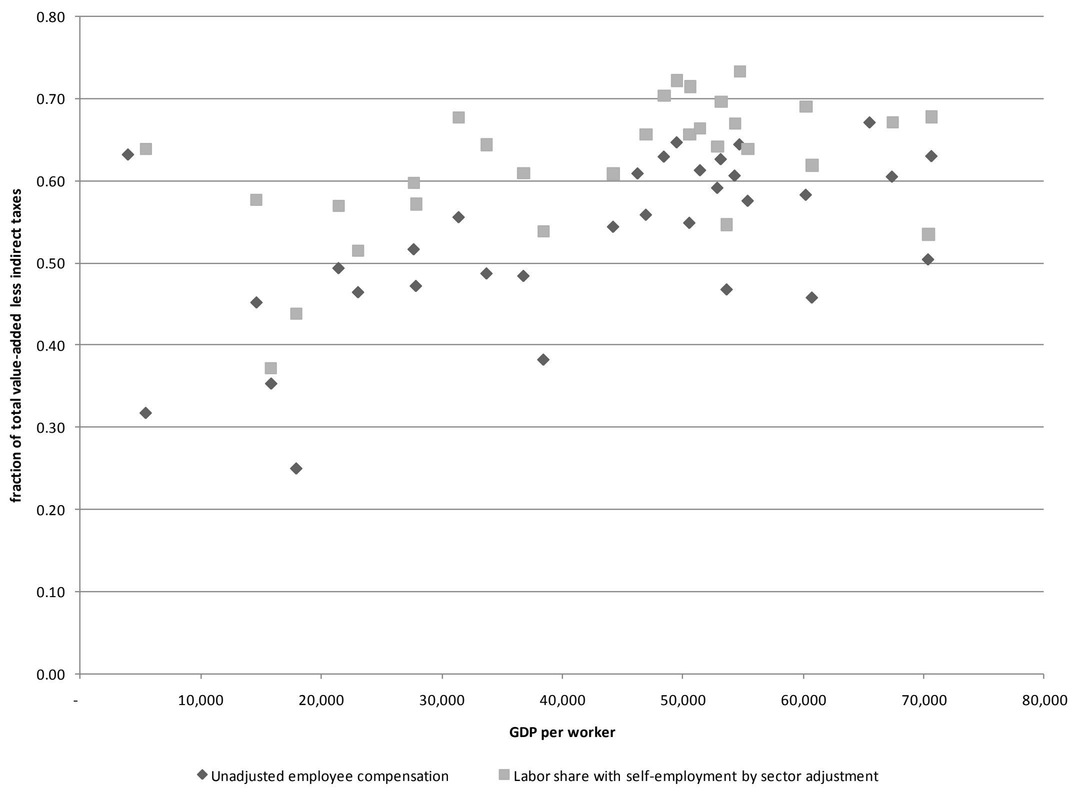

Fig. 1. Share of unadjusted employee compensation compared to labor share with self-employment adjustment by sector.

The difference in the labor share estimates when the distribution of self-employment *by sector* is taken into consideration highlights a significant structural difference between the economies of developing and developed countries: the relative size and productivity of the agricultural sector. Table 2 shows the relative importance of agriculture in employment and self-employment. For all the countries in this sample, the agricultural sector has a disproportionate share of the self-employed, but this is particularly noteworthy in developing countries. In these countries, agriculture is both a prominent employer and is far less productive than the non-agriculture sectors of the economy, indicated by the high ratio of value-added per worker outside

TABLE 2

Employment and self-employment in agriculture

Country, ranked from lowest to highest GDP per worker	Agriculture employment / total employment	Self-employment in agriculture / employment in agriculture	Value-added per worker in non-agriculture sectors / value-added per worker in agriculture	Self-employment / total employment
China	0.61	-	6.81	-
Indonesia	0.45	0.58	4.14	0.67
Brazil	0.21	0.39	2.85	0.38
Russia	0.10	0.47	1.44	0.07
Turkey	0.43	0.72	4.88	0.56
Poland	0.17	0.61	5.00	0.25
Slovak Republic	0.06	0.04	1.12	0.10
Hungary	0.05	0.13	1.22	0.14
Czech	0.05	0.10	1.28	0.17
Portugal	0.12	0.40	3.48	0.26
Korea	0.11	0.27	2.73	0.38
New Zealand	0.10	0.28	1.40	0.21
Greece	0.15	0.38	1.98	0.38
Finland	0.05	0.28	1.09	0.13
Spain	0.07	0.19	2.02	0.19
Japan	0.05	0.26	2.89	0.17
United Kingdom	0.02	0.06	1.46	0.12
Australia	0.05	0.15	1.47	0.17
Sweden	0.02	0.15	1.16	0.10
Denmark	0.03	0.20	1.25	0.08
Austria	0.06	0.37	2.35	0.13
Israel	0.02	0.08	1.02	0.14
Ireland	0.09	0.36	1.62	0.19
Germany	0.03	0.12	1.96	0.11
Canada	0.03	0.12	1.56	0.16
Netherlands	0.03	0.15	1.27	0.11
Belgium	0.02	0.09	1.24	0.16
Italy	0.06	0.12	1.91	0.27
Switzerland	0.04	-	3.06	-
France	0.04	0.25	1.37	0.11
Norway	0.04	0.35	1.76	0.07
USA	0.03	0.13	2.04	0.07

Source. ILO Laborsta Table 1.C. for self employment; OECD input-output tables for value-added by sector; employment by sector for China and Switzerland based on ILO Laborsta Table 1.E. Taiwan is excluded from this table since it does not report employment by sector.

of agriculture compared to that in agriculture. Since the seminal work of W. Arthur Lewis (1954) the relative backwardness of agriculture has been a stylized fact of economic development, a status confirmed more recently by Gollin et al. (2004). I return to this topic below and show how uneven technological progress influences the measurement of economy-wide factor productivity.

Once an accurate share of labor income, α_L, is determined, the share of capital income is presumably equal to one minus the labor share, $1-\alpha_L$. Here again there is controversy about exactly what this measures. Caselli and Feyrer (2007) argue that $1-\alpha_L$ in fact measures the payment share of total wealth, which includes non-reproducible assets such as cropland. Based on data in World Bank (2006), they note that the share of produced capital is around half that of total wealth, and varies inversely with GDP per worker.[5] The corresponding payment share of produced capital would thus be equal to $0.55(1-\alpha_L)$ for the typical country, a substantial adjustment. A pertinent question is thus whether this large stock of natural wealth is actually generating income recorded in value-added payments.

Some insight on this question can be gained by comparing gross operating surplus (GOS) generated outside the natural resource-intensive sectors as a share of total GOS. I assume that the only natural resource - earning sectors are agriculture, forestry and fishing, and mining, and, like Caselli and Feyrer, I assume that produced and natural capital earn the same rate of return. Under these assumptions, the share of total GOS paid to non-natural resource sectors should actually be lower than the World Bank's estimated share of produced capital and urban land in

[5] Total wealth as used here and by Caselli and Feyrer includes only natural capital, produced capital and urban land, as reported in World Bank (2006) Appendix 2, page 159 for the year 2000. The World Bank assumes urban land is equal to 24 % of produced capital for all countries and does not report data for four countries in this sample (the Czech Republic, Poland, the Slovak Republic, and Taiwan).

total wealth, since some share of produced capital must be employed in the natural resource-intensive sectors. However, the data presented in Figure 2 show that in fact the share of GOS is typically higher than the share of reproducible capital, especially in countries with a high share of natural resource wealth.[6] There are several possible explanations for this discrepancy: the World Bank measure of natural resources likely includes non-earning assets, and rents to owner-occupied land may not be recorded in GOS. In the absence of more accurate data on the share of income actually paid to reproducible capital, I assume here that payments to reproducible capital are equal to $1-\alpha_L$.

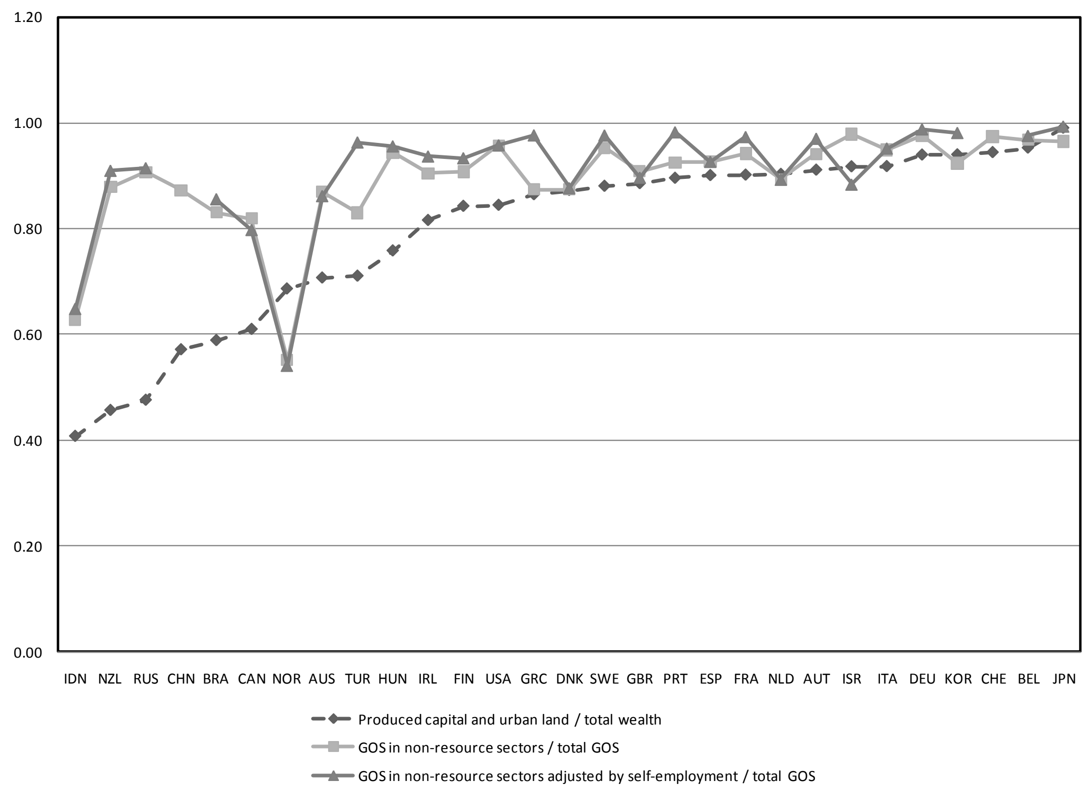

Fig. 2. World Bank (2006) estimate of produced capital and urban land as share of total wealth in the year 2000 compared to share of gross operating surplus (GOS) from non-resource intensive sectors to total GOS.

[6] The main exception is Norway, which appears to fully account for its substantial North Sea oil and gas earnings in the mining sector.

To measure the produced capital stock, I take into account differences in local prices of capital goods compared to output goods emphasized by Caselli and Feyrer by using the United Nations *National Income and Product Account* (NIPA) statistics, given in local prices, rather than the more commonly used Penn World Table data, which converts local prices to international prices. Further details on the computation of the capital stock are in the Data Appendix. Figure 3 depicts the average wage, computed by dividing the adjusted labor share by total employment in each country and converted to purchasing power parity dollars, matched with the rental rate to capital computed in an analogous fashion for the 33 countries in this sample.

The resulting wage rental ratio seems surprisingly diverse. About half the sample, typically high income countries, has a wage rental ratio above that of the United States. Many low income countries have low wages but relatively high rental rates and so have substantially lower wage rental ratios than the United States. In the simple framework of productivity-adjusted factor price equality, this rules out a single Hicks neutral productivity parameter that does not vary between factors, as has been employed widely in the Heckscher Ohlin Vanek literature (see Trefler, 1995, Davis and Weinstein, 2001, Debaere, 2003). An adequate analysis of international productivity differences must also include an explanation for this distinctive pattern in wage rental ratios.

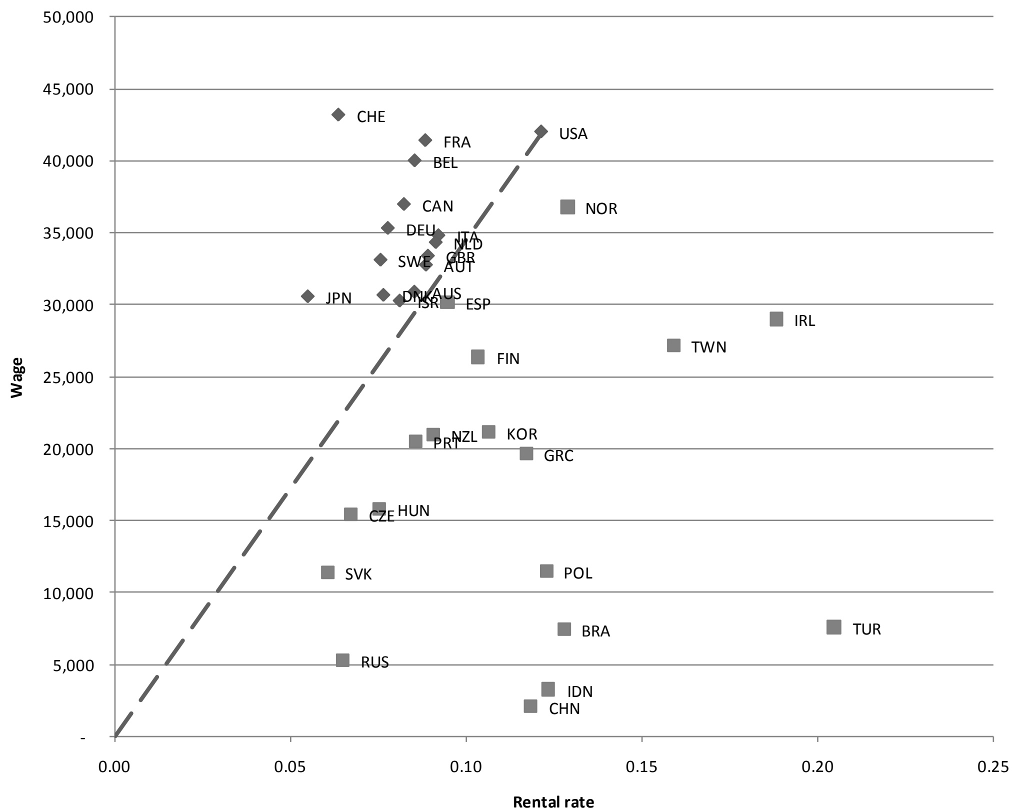

Fig. 3. Average factor payments for labor and capital across countries

III. 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_d be the f by n technology matrix for country d, 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 d can be compared to that of a reference country c such that $a_{fic} = \pi_{fid} a_{fid}$, where π_{fid} is the factor-specific difference in productivity for industry i. Factor-specific but industry neutral differences in productivity imply $\pi_{fid} = \pi_{fjd}$ for all industries, so the factor-specific productivity is denoted simply by π_{fd}.

I propose a simple measure of π_{fd} that both allows for across industry variation and can be measured with only the reference country technology matrix, given data on the total endowments, v_d, and output by sector, y_d, for country d. Define the virtual endowment $\tilde{v}_d$ as the vector of factors that would be used by the reference country to produce country c's output, so that $\tilde{v}_d = A_c y_d$. The factor specific productivity can then be computed by $\pi_{fd} = \tilde{v}_{fd} / v_{fd}$, where $\tilde{v}_{fd}$ and v_{fd} are the f^{th} elements in the respective endowments vectors, and Π_d is the f by f diagonal matrix of π_{fd}.

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 $\Pi_d A_d = A_c$. In the more general case that industries vary in their use of factors across countries, then $\Pi_d A_d \neq A_c$, although by construction $\Pi_d A_d y_d \equiv A_c y_d$. 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.

The accuracy of this index of factor-specific productivity depends in large part on the accuracy of the reference country technology matrix. The United States was chosen as the reference country since there is data on factor use by detailed sector provided by the United States Bureau of Economic Analysis (BEA) for capital and the Bureau of Labor Statistics (BLS) for labor. I tested two alternative measures of the U.S. technology matrix. The first measure allocates capital by sector according to the value-added paid to capital recorded in the OECD input-output table, adjusted by self-employment by sector. The second measure uses the BEA data for private and government fixed assets adjusted to match the input-output sectors. There was little appreciable difference in the resulting productivity estimates, so I focus on the results using the first value-added based technology matrix, with a few observations on the alternative BEA results where relevant. The labor data by sector is based on detailed BLS occupational data by sector with a somewhat more crude adjustment for self-employment, equal to about 7% of the U.S. labor force. Further details on the data sources and computation of the U.S. technology matrix are given in the Data Appendix.

If productivity differences are uniform across industries there is a clear and simple relationship between factor-specific productivity and factor payments. Under the assumption of zero profits and exogenous world prices p, then $p = A_d^T w_d$, where w_d is the factor payment vector for country d. This implies that $A_c^T w_c = A_d^T w_d$, where A_c is the U.S. Leontief matrix and w_c is the U.S. factor payment vector. If $\Pi_d A_d = A_c$, then $A_d^T w_d = A_d^T \Pi_d w_c$, which in turn implies that $w_d = \Pi_d w_c$.[7] That is, 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. Following Trefler (1993), a visual representation of the data for both labor and capital is presented in Figure 4.

I also replicate Trefler's regressions of country d's wage w_{Ld} and rental rate w_{Kd} on the productivity of labor π_{Ld} and capital π_{Kd} relative to the U.S. in logarithms. According to productivity-adjusted factor price equalization, the coefficient on the log of each productivity parameter should equal one. The results are as follows (standard errors are in parenthesis):

$$\log(w_{Ld}) = \underset{(0.03)}{3.73} + \underset{(0.03)}{1.11} \log(\pi_{Ld}), \quad R^2 = 0.97$$

$$\log(w_{Kd}) = \underset{(0.047)}{-2.14} + \underset{(0.11)}{0.73} \log(\pi_{Kd}), \quad R^2 = 0.58$$

The reverse regressions, which account for errors in the measurement of productivity, give a probability limit for the true coefficient on $\log(\pi_{Ld})$ of [1.11, 1.14] and on $\log(\pi_{Kd})$ of [0.73, 1.25]. Hence one can reject the hypothesis that factor-adjusted factor price equalization holds for labor, and although the probability limit for the coefficient on capital productivity includes 1, it is estimated with much less precision.[8] Oddly the results for labor are opposite from Trefler in that he found the asymptotic range of the coefficient on $\log(\pi_{Ld})$ was below one.

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

[8] The regression results for capital based on the alternative BEA-based U.S. technology matrix – which differs only for capital- showed a slightly wider probability limit of [0.6,1.39] and an R^2 of 0.43.

Furthermore, although the hypothesis of productivity-adjusted factor price equalization for labor is technically rejected, there is clearly a tight relationship between w_{Ld} and π_{Ld} that begs explanation.

Several other important distinctions between these results and those published in Trefler (1993) must be emphasized. First and foremost, the productivity parameters used here are estimated from actual data on technology and factors, not imputed from trade data to fit the Heckscher-Ohlin-Vanek (HOV) prediction. Trefler's results showed a strong positive correlation between the productivity of capital and labor, whereas I find that the productivity of capital shows no correlation with the productivity of labor, in general accord with the observed wage rental ratios. This draws into question Trefler's suggested explanation that these productivity differences stem from national differences in industriousness and technology. Finally, there is a distinctive pattern in the prediction error between productivity and factor payments clearly visible in Figure 4: those countries with low wage rentals tend to fall below the diagonal line in the labor diagram but above the diagonal line in the capital diagram. The reverse is true for those countries with high wage rental ratios. In the next section I shall discuss an alternative explanation for factor-specific productivity differences that explains both the observed correlation between factors productivities and the pattern of prediction error between the high and low wage rental country groups.

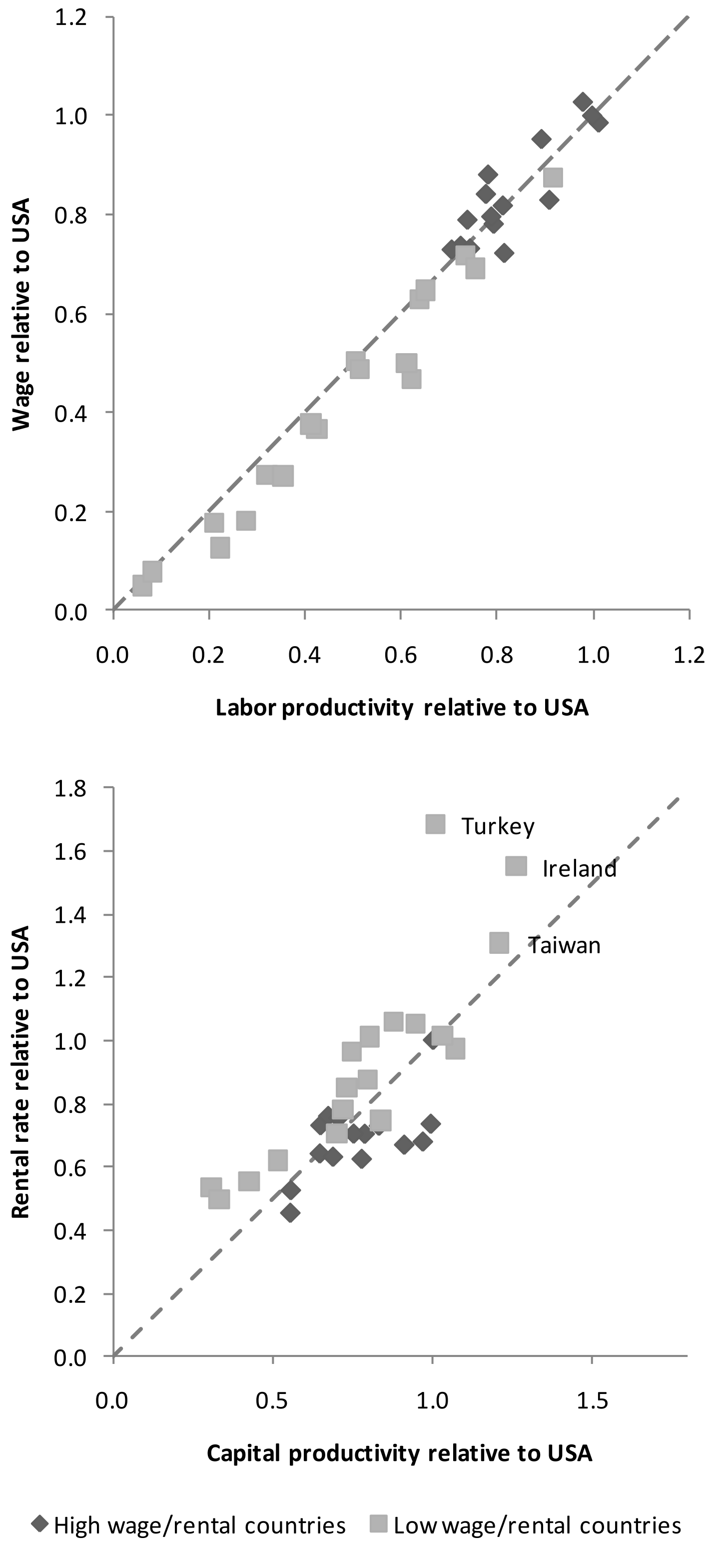

Fig. 4. Factor payments and factor productivity

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

To motivate my empirical analysis, I first present a highly stylized theoretical framework intended to explain why countries with low labor productivity may also have high capital productivity. Consider a two-sector, two factor model with a constant elasticity of substitution (CES) unit production function for industry i as follows

$$1 = \theta_i \left[\delta_i \ell_i^{-b} + (1-\delta_i) k_i^{-b} \right]^{-1/b} \tag{2}$$

where ℓ_i is the unit input requirement of labor in industry i, k_i is the unit input requirement of capital in industry i, δ_i is the distribution share of labor in industry i, and θ_i is total factor productivity in industry i relative to a reference country at the technology frontier. The elasticity of substitution between factors is given by $\sigma \equiv \dfrac{1}{1+b}$, which is assumed to be the same across industries. Assume that only total factor productivity in each industry varies between the two countries, so that δ_i and σ are the same across countries. The two industries represent a traditional or labor intensive sector, such as agriculture, and a modern or capital intensive sector, such as manufacturing. I also assume both countries produce and trade both goods at an exogenously determined world price.

The standard profit maximization assumptions used to derive the unit labor demand as a function of the wage can be used to construct a comparison of labor input coefficients between two countries in industry i:

$$\frac{\ell_{ic}}{\ell_{id}} = \left(\frac{w_{Ld}}{w_{Lc}}\right)^{\sigma} \left(\frac{\theta_{id}}{\theta_{ic}}\right)^{1-\sigma} . \qquad (3)$$

An analogous equation in terms of the relative rental rates describes the capital input coefficients. To simplify notation let the combined country subscripts dc indicate the ratio of a given variable in country d and the same variable in country c. Using this notation, Equation (3) becomes $\ell_{icd} = w_{Ldc}^{\sigma}\theta_{idc}^{1-\sigma}$.

Equation (3) shows that differences in factor usage will be industry-neutral if $\sigma = 1$, as in the special Cobb-Douglas case. In this case the factor payment shares in each country will be equal in each industry and the country with the lower wage will use relatively more labor, which will in turn lead to an industry-neutral pattern of factor-specific productivity differences between the two technology matrices given by

$$A_c = \begin{bmatrix} w_{Ldc} & 0 \\ 0 & w_{Kdc} \end{bmatrix} A_d \qquad (4)$$

where A_c is the f by n technology matrix of country c. Expressed in terms of the factor-specific productivity notation, $\Pi_{dc} = \begin{bmatrix} w_{Ldc} & 0 \\ 0 & w_{Kdc} \end{bmatrix}$. In the general equilibrium setting, the sector-specific differences in total factor productivity will determine the differences in factor payments which in turn determine Π_{dc}. A country with relatively low wages will use more labor in all industries, which would be interpreted as low labor productivity by the factor-specific productivity measure.

A graphical interpretation of this framework using isocost lines is given in Figure 5. Point b represents a low wage country that has uniformly lower TFP in both sectors compared to a high wage country, represented by point c. Country b should exhibit the same relative factor prices as Country c, exactly proportional to the difference in TFP. However, if the "traditional" or labor intensive sector is relatively more backward than the "modern" or capital intensive sector, the country will be represented by point d, and the wage rental ratio will be below 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. Since the productivity matrix is determined by the relative factor payments, capital will be measured as more productive since less will be used in production in both industries in comparison to the high wage country.

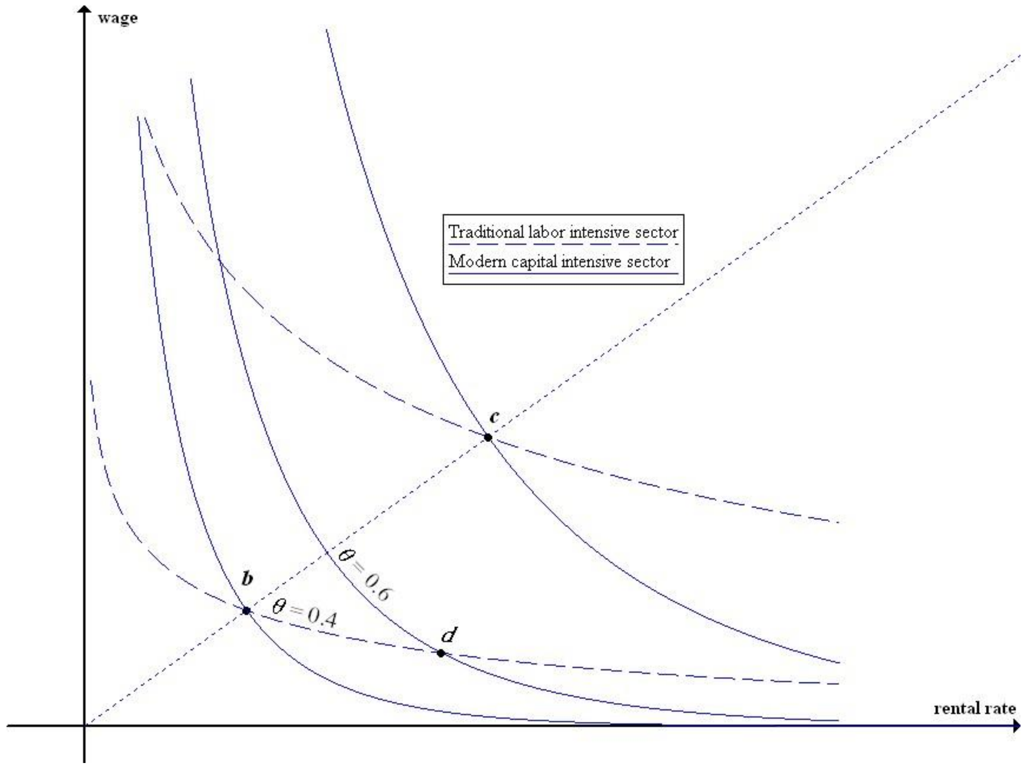

Fig. 5. Uneven technological development in a two-sector model, drawn with CES isocost curves and σ = 0.9.

Under the assumption of zero profits and exogenous world prices p, $p = A_c^T w_c = A_d^T w_d$ so $w_c = \Pi_{dc} w_d$. The measure of virtual endowments in this simple theoretical framework is given by $\tilde{v}_d = A_c y_d$, where y_d is country d's output vector and v_d. The factor-specific productivity matrix Π_{dc} is equal to the ratio of virtual endowments to actual endowments, expressed as $\tilde{V}_d V_d^{-1}$, where $\tilde{V}_d$ and V_d are the diagonal matrices of the virtual endowments and actual endowments respectively.

Next consider the case when the elasticity of substitution between factors is less than 1. The technology matrix of country c can be compared to country d by

$$A_c = \begin{bmatrix} w_{Ldc}^{\sigma}\theta_{1dc}^{1-\sigma}\ell_{1d} & w_{Ldc}^{\sigma}\theta_{2dc}^{1-\sigma}\ell_{2d} \\ w_{Kdc}^{\sigma}\theta_{1dc}^{1-\sigma}k_{1d} & w_{Kdc}^{\sigma}\theta_{2dc}^{1-\sigma}k_{2d} \end{bmatrix} = \begin{bmatrix} w_{Ldc}^{\sigma} & 0 \\ 0 & w_{Kdc}^{\sigma} \end{bmatrix} A_d \begin{bmatrix} \theta_{1dc}^{1-\sigma} & 0 \\ 0 & \theta_{2dc}^{1-\sigma} \end{bmatrix}. \tag{5}$$

The relationship between wages in the two countries can no longer be summarized by a single diagonal matrix, as in the Cobb-Douglas case. However, in the case of uneven technological change the virtual endowment productivity measure will have a specific bias in relation to the true relative factor payments. The virtual endowment measure of factor-specific productivity can now be expressed as

$$\tilde{V}_d V_d^{-1} = \begin{bmatrix} w_{Ldc}^{\sigma}\hat{\theta}_{dc} & 0 \\ 0 & w_{Kdc}^{\sigma}\hat{\theta}_{dc} \end{bmatrix} \tag{6}$$

where $\hat{\theta}_{dc}$ is a weighted average of $\theta_{1dc}^{1-\sigma}$ and $\theta_{2dc}^{1-\sigma}$.[9] This productivity measure will no longer equal the relative factor payments. However, using the values in Figure 5, note that $w_{Ldc} < 0.4$ and $w_{Kdc} > 0.6$. Hence, it must be the case that $w_{Ldc}^{\sigma}\hat{\theta}_{dc} > w_{Ldc}$ and $w_{Kdc}^{\sigma}\hat{\theta}_{dc} < w_{Kdc}$ since $0.4^{1-\sigma} < \hat{\theta}_{dc} < 0.6^{1-\sigma}$. If a country has higher TFP in the labor intensive sector compared to the capital intensive sector, and thus has a higher relative wage-rental ratio than country c, it is straightforward to show the direction of these biases in the virtual endowment productivity

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[9] This generalizes easily to the f by n case. The typical diagonal element of $\tilde{V}_d V_d^{-1}$ is equal to $w_{fdc}^{\sigma}\sum_{i=1}^{n}\theta_{idc}^{1-\sigma}\varpi_{fi}$ where $\varpi_{fi} = \frac{a_{fi}y_i}{v_f}$ and a_{fi}, y_i, and v_f are elements in A_d, y_d, and v_d respectively. Under the assumption of full employment $v_f = \sum_{i=1}^{n} a_{fi}y_i$ so that $\sum_{i=1}^{n}\varpi_{fi} = 1$, and if at least 2 industries use factor f, $0 < \varpi_{fi} < 1$.

measures will be reversed. In the multi-sector case, a country with a low wage-rental ratio relative to the reference country will have $\theta_{\min}^{1-\sigma} < \hat{\theta}_{dc} < \theta_{\max}^{1-\sigma}$ where $\theta_{\min}$ is the labor-intensive sector with the lowest relative TFP and $\theta_{\max}$ is the more capital intensive sector with the highest TFP. In this case, the number of iso-cost curves that intersect at point d is equal to the number of sectors and the direction of the bias between the virtual endowment measure of factor productivity and factor payments to labor and capital will be the same.

This framework motivates an empirical evaluation of the prediction bias observed between the measure of factor productivity based on virtual endowments and the relative factor payment. If a country has a low wage rental ratio, a binomial sign test generates a "correct" prediction when the virtual endowment measure of labor productivity is above the relative wage, and the virtual endowment capital productivity is below the relative rental rate. The reverse is predicted when the country has a high relative wage rental ratio. The results, presented in Table 3, show a highly significant success rate for both factors.[10] Industry variations in TFP together with less than unitary substitution between labor and capital can explain the failure of productivity-adjusted FPE for labor in the presence of a high degree of correlation between the productivity measure and relative wages, and the noticeable pattern of prediction errors depicted in Figure 4.

[10] The sign test for capital using the BEA-based U.S. technology matrix to predict productivity was slightly higher with 28 "correct" guesses.

TABLE 3

Factor productivity measured by virtual endowment and factor payments relative to the United States

Country	Labor Productivity	Wage	Sign Test of prediction error	Country	Capital Productivty	Rental Rate	Sign Test of prediction error
Countries with High Wage Rental Ratios							
Australia	0.72	0.74	1	Australia	0.79	0.70	1
Austria	0.79	0.78	0	Austria	0.65	0.73	0
Belgium	0.89	0.95	1	Belgium	0.75	0.70	1
Canada	0.78	0.88	1	Canada	0.97	0.68	1
Denmark	0.74	0.73	0	Denmark	0.69	0.63	1
France	1.01	0.99	0	France	0.83	0.73	1
Germany	0.78	0.84	1	Germany	0.65	0.64	1
Israel	0.82	0.72	0	Israel	0.91	0.67	1
Italy	0.91	0.83	0	Italy	0.67	0.76	0
Japan	0.71	0.73	1	Japan	0.56	0.45	1
Netherlands	0.81	0.82	1	Netherlands	0.71	0.75	0
Sweden	0.74	0.79	1	Sweden	0.78	0.62	1
Switzerland	0.98	1.03	1	Switzerland	0.56	0.52	1
United Kingdom	0.79	0.79	1	United Kingdom	0.99	0.73	1
Countries with Low Wage Rental Ratios							
Brazil	0.21	0.18	1	Brazil	0.95	1.05	1
China	0.06	0.05	1	China	1.07	0.97	0
Czech Republic	0.42	0.37	1	Czech Republic	0.43	0.55	1
Finland	0.64	0.63	1	Finland	0.73	0.85	1
Greece	0.62	0.47	1	Greece	0.75	0.96	1
Hungary	0.41	0.38	1	Hungary	0.52	0.62	1
Indonesia	0.08	0.08	1	Indonesia	1.03	1.02	0
Ireland	0.76	0.69	1	Ireland	1.26	1.55	1
Korea	0.50	0.50	1	Korea	0.80	0.88	1
New Zealand	0.61	0.50	1	New Zealand	0.84	0.75	0
Norway	0.92	0.88	1	Norway	0.88	1.06	1
Poland	0.32	0.27	1	Poland	0.80	1.01	1
Portugal	0.51	0.49	1	Portugal	0.70	0.71	1
Russia	0.22	0.13	1	Russia	0.31	0.53	1
Slovak Republic	0.35	0.27	1	Slovak Republic	0.33	0.50	1
Spain	0.73	0.72	1	Spain	0.72	0.78	1
Taiwan	0.65	0.65	1	Taiwan	1.21	1.31	1
Turkey	0.28	0.18	1	Turkey	1.01	1.69	1
Total Correct predictions			27				26
Binomial probability, n=32			< 0.000				< 0.000

B. Empirical evaluation of technology differences between industries

I have argued that a specific pattern of cross-country variations in TFP between broad sectors such as agriculture and manufacturing can explain the relation of measured factor productivities to factor payments among this diverse group of 33 economies. So far the evidence has been circumstantial, and it would be useful to directly measure industry-level TFP to further test this hypothesis. I follow the approach of Harrigan (1999), who illuminates Caves et al. (1982)'s presentation of the Tornqvist-Theil-translog TFP index and uses it to document large industry-specific differences in TFP in a group of 8 industrial countries. Other important studies that highlight industry-specific differences in TFP among a wider range of countries, such as Yeaple and Golub (2007) and Lai and Zhu (2007), focus as does Harrigan on the manufacturing sector. At the other extreme of aggregation, Hall and Jones (1999) and Parente and Prescott (2000) argue convincingly that macro-level differences in TFP explain the wealth and poverty of nations.[11]

In principal, the OECD input-output data allow TFP at the industry level to be estimated in the same manner as a macro-level production function that expresses output as a function of primary factors only. Each of the n columns in the technology matrix A_c is the set of f factors necessary to produce one unit of output in the n^{th} industry based on both direct factor inputs and indirect intermediate inputs which are in turn produced by direct factors. Assuming constant returns to scale, this provides the key data on factor usage necessary to estimate total factor productivity at the industry level. The data constraint for many countries is direct factor usage by

[11] To some degree this bi-polar pattern of study reflects major data limitations. As Harrigan (1999, page 269) observes, the gold standard in TFP measurement pioneered by Jorgenson and various coauthors (1987, 1990) has been applied in practice to only few countries. The challenges hinge on obtaining a complete picture of all inputs into production, and on having accurate price deflators to adjust for different prices across countries, sectors, and time.

sector. For labor, the International Labor Office publishes employment data by sector at a fourteen sector level of aggregation for most of the countries in the sample. Capital use by sector can be inferred from the value-added payments to capital divided by the economy-wide rental rate.

Obtaining detailed price data by sector, the importance of which is emphasized by Harrigan, is far more problematic. To compare output vectors across countries I have relied on the most recent International Comparison Project purchasing power parity (PPP) exchange rates, which represent an exhaustive effort to accurately compare GDP across countries. As detailed by World Bank (2008), the PPP exchange rates equate the cost of a diverse basket of over 1000 goods and services. However, I have converted the output of all sectors by the same PPP exchange rate, a procedure that assumes the relative price of goods by sector does not differ from the US, the reference country for the purchasing power parity estimates. If a specific sector's price level is overestimated, as might be the case with non-traded goods in low wage countries, its output will be underestimated and consequently TFP will be underestimated. This bias in the estimation of TFP will amplify my own hypothesis to the extent that non-traded goods are labor intensive, as is commonly assumed. Unfortunately, given the state of price indexes by production sector for this sample of countries, there is no solution to this problem that would not introduce as much noise itself into the TFP measures.

The computation of the Tornqvist-Theil-translog TFP is straight-forward using data on direct and indirect factor usage and factor payment shares by sector. The most desirable feature of this index is that it allows for different factor payment shares across industries, as would occur with the CES production function in Equation (2). Let ℓ and k represent the direct and indirect labor and capital input requirements to produce one unit of industry i output, so the TFP of country d relative to country c is given by:

$$TFP_{dc} = \left(\frac{\bar{\ell}}{\ell_d}\right)^{\alpha_d} \left(\frac{\bar{k}}{k_d}\right)^{1-\alpha_d} \left(\frac{\ell_c}{\bar{\ell}}\right)^{\alpha_c} \left(\frac{k_c}{\bar{k}}\right)^{1-\alpha_c} \tag{7}$$

where a bar denotes an average value, and $\alpha_j = {(s_j + \bar{s})}/{2}$ where s_j is the labor share of total cost. Table 4 presents the resulting TFP measures for a selection of two large countries with very low wage rental ratios, Indonesian and Brazil, and two large countries with very high wage rental ratios, Japan and France.

TABLE 4
Total factor productiviy by broad sector (United States = 100)

Description (ISIC Rev. 3 Industry Code)	Brazil	Indonesia	France	Japan
Agriculture (A, B)	28	13	100	56
Mining (C)	57	57	84	33
Manufacturing (D)	40	21	92	59
Utilities (E)	72	41	89	52
Construction (F)	41	21	91	64
Wholesale and retail trade (G)	28	18	89	63
Hotels and restaurants (H)	43	23	135	81
Transport and communications (I)	37	17	81	58
Financial Intermediation (J)	50	37	90	49
Real estate (K)	54	37	89	52
Public adminisitration (L)	64	20	112	112
Education (M)	26	15	117	102
Health (N)	21	17	77	68
Other services (O, P, Q)	10	7	49	48

The computations confirm a wide range of TFP between the broad industry groups. A test of the hypothesis depicted in Figure 5 is presented in Table 5. For each country, the results of a regression of TFP normalized by its average value on a constant and the normalized capital labor ratio in each industry are presented, allowing only 14 observations per regression. The hypothesis predicts a positive coefficient on the capital labor ratio for countries with low wage rental ratios and a negative coefficient for countries with high wage rental ratios. The results are statistically significant in only 5 of 31 regressions. However, all 5 significant results have the predicted signs and are for countries with the lowest wage rental ratios, countries with large agricultural sectors that would thus be expected to have the largest divergence in TFP across industries. Likewise, there are no positive coefficients among the 14 countries with high wage rental ratios, although these results are not statistically significant.

This section has presented a somewhat cursory look at the measurement of TFP using the same OECD input-output tables used to measure factor-specific productivity, combined with very basic measures of sector-specifc inputs. I show that large differences in TFP across industries broadly substantiate a process of uneven development, especially in the countries with the lowest wage rental ratios , and provide further evidence that countries' technology matrices embody industry-specific variations in production technology.

TABLE 5
Regression of total factor productivity on capital labor ratio by industry

from lowest to highest wage rental ratio	Coefficient	(Standard Error)		R^2
Countries with high wage rental ratios				
Switzerland	-0.05	(0.08)		0.03
Japan	-0.13	(0.10)		0.13
Belgium	-0.09	(0.09)		0.07
France	-0.04	(0.09)		0.02
Germany	-0.07	(0.06)		0.09
Canada	-0.02	(0.05)		0.01
Sweden	-0.05	(0.06)		0.06
Denmark	-0.01	(0.03)		0.01
Italy	-0.05	(0.09)		0.03
Netherlands	-0.01	(0.03)		0.01
United Kingdom	-0.03	(0.04)		0.05
Israel	-0.09	(0.10)		0.06
Austria	-0.06	(0.10)		0.03
Australia	-0.03	(0.04)		0.05
Countries with low wage rental ratios				
Spain	-0.02	(0.11)		0.00
Norway	0.01	(0.03)		0.02
Finland	-0.04	(0.08)		0.02
Portugal	0.09	(0.08)		0.09
New Zealand	0.06	(0.04)		0.12
Czech Republic	-0.01	(0.09)		0.00
Hungary	0.06	(0.07)		0.05
Korea	0.10	(0.07)		0.16
Slovak Republic	0.16	(0.08)	*	0.28
Greece	0.02	(0.06)		0.01
Ireland	0.03	(0.08)		0.01
Poland	0.15	(0.11)		0.14
Russia	0.15	(0.11)		0.17
Brazil	0.32	(0.08)	***	0.60
Turkey	0.34	(0.05)	***	0.80
Indonesia	0.33	(0.04)	***	0.87
China	0.52	(0.08)	***	0.77

* *Significant at 10 percent level*

** **Significant at 1 percent level*

Notes. The reported coefficient is $\widehat{\beta}_1$ in the OLS regression of $TFP_i = \beta_0 + \beta_1 \left(k_i / \ell_i \right) + \varepsilon_i$, where each observation is one of 14 sectors (listed in Table 4). Variables are normalized by their average value in each country.

V. Conclusion

Most of the international variations in factor payments can be explained by variations in simple measures of factor-specific productivity. However, the exact relationship between the measured productivity parameters and factor payments does not support productivity-adjusted FPE unambiguously. Instead, I argue that the productivity measures approximate underlying differences in technology that are rooted in the type of economic activity. Industry-specific variations in TFP across broad sectors and less than unitary substitutability between factors can better explain these technology differences and the resulting pattern of international factor payments than differences inherent in factors or common across economies.

OECD input-output data on value-added by sector also permit a critical examination of the labor and natural resource share of income. The lowest wages are in those countries with large agricultural sectors in which the self-employed are concentrated, and an accurate measure of the labor share of income should take these variations in value-added per worker across sectors into account. It is not clear to what degree resource rents augment the payment to produced capital in natural resource sectors, but measures of wealth intended to document the complete stock of potentially valuable natural assets are inaccurate measures of recorded value-added payments. When measured correctly, average factor payments across countries confirm a wide variation in wage rental ratios that can not be explained by a single industry-neutral productivity parameter, as is often employed in the HOV literature.

The empirical failure of the elegant HOV theory of international trade has motivated the search for a simple parameterization of international technology differences. The results presented here do not rule out a modified version of the HOV model that can explain the factor content of trade. At the very least it is necessary to permit productivity to vary between factors when comparing the technology matrices of countries at different stages in economic development. The provacative work of Parente and Prescott (2000) on the importance of TFP has spurred more detailed study into the underlying source of variations in TFP between industries and firms across countries. My results suggest there is much common ground between this area of research and a better formulation of the HOV paradigm in international trade.

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Data Appendix

Purchasing power parity exchange rates for the year 2005 are from the World Bank (2008), converted to match each country's input-output table year (IOY) according to

$e_{c,IOY} = e_{c,2005} \prod_{t=1}^{T} \frac{1+\dot{P}_{USA,2005-(t-1)}}{1+\dot{P}_{c,2005-(t-1)}}$, where the second subscript in all variables refers to the year of observations, $e_{c,2005}$ is the purchasing power exchange rate reported by the World Bank for country c , $T = 2005 - IOY$, and $\dot{P}_c$ is the annual inflation rate measured by the GDP deflator for country c given in World Bank's World Development Indicators (or in the case of Taiwan from the economic data web site www.econstats.com). The resulting values are converted to base year 2000 by dividing by the GDP deflator for the U.S. published in the Economic Report of the President (2007).

Self-employment data are taken from Table 1.C. *Economically active population, by industry and status in employment* published on the International Labour Organization's data website at http://laborsta.ilo.org for the available year closest to the input-output (IO) year. The available year matched the input-output year for 14 countries and for the remaining 16 reporting countries the year was within 5 year of the input-output year. The self-employment data was typically reported for 17 broad sectors based on ISIC Rev. 3 categories A through Q which could then be matched to 15 aggregated input-output sectors, since the input output tables aggregate sector A with B and sector P with Q. Some countries (Indonesia, New Zealand, Japan, Turkey and the United States) report self-employment data for 9 sectors based on ISIC Rev. 2 and the IO value-added was aggregated accordingly. The self-employment correction caused the labor share to exceed 1 in 81 sectors (typically sectors M through Q),or about one third of the total number of sectors for which self-employment is reported. The value in these sectors was set at a maximum value of 0.9.

Three countries (China, Switzerland, and Taiwan) do not report self-employment data by sector for recent years. However, for China, the employee compensation as share of value added less indirect taxes in the agriculture sector was equal to 0.9, compared to only 0.45 in Brazil and 0.09 in Indonesia. In Taiwan and Switzerland the emloyee compensation in agriculture was 0.67 and 0.41 respectively. Since these figures do not seem out of line with the adjusted measures for agriculture and any correction would be somewhat arbitrary, I used the unadjusted total employee compensation to compute the labor share in all three countries.

Employment data for each country's total labor endowment was taken from ILO Laborsta Table 1.E. *Economically active population, by industry and by occupation*, since data in this table could be more closely matched to the input output reporting year, and it was also used in the TFP computations for emplyment by sector.

The U.S. Bureau of Economic Analysis publishes fixed assets for the private sector by industry (Table 3.1ES. *Current-Cost Net Stock of Private Fixed Assets by Industry*) and for total government assets (Table 7.1B. *Current-Cost Net Stock of Government Fixed Assets*) on their website at www.BEA.gov , which was the point of departure for the construction of the U.S. technology matrix. Two versions of this matrix were constructed because the BEA industry categories, based on the 1997 North American Industry Classification System, do not correspond exactly to the ISIC Ver. 3 industry categories used in the OECD IO tables. I used the sum of total fixed assets from the BEA tables 3.1ES and 7.1B for the year 2000, equal to about $27 trillion, to infer the average rental rate for the U.S. capital and the rate of depreciation of capital stock for all countries in the sample, as discussed below.

To compute the value-added version of the U.S. technology matrix I first constructed a self-employment adjustment using Equation (1) for 14 broad sectors based on ILO Table 1.C for the U.S. for the year 2004. I assumed that the self-employment share was the same in the more detailed IO sectors; for example the share of workers who are self-employed in the U.S. manufacturing sector is 1.8 percent, which was applied to all 22 manufacturing sub-sectors reported in the IO table. The economy wide rental rate, equal to 0.121, was based on the sum of the self-employment adjusted GOS divided by the total BEA capital stock. The capital stock by sector was then imputed by dividing the self-employment adjusted GOS in each sector by the economy-wide rental rate.

The alternative U.S. technology matrix is based directly on the BEA Table 3.1ES, redistributed to IO sectors where necessary based on the value-added shares. The government fixed assets, at $5.7 trillion representing over 20 percent of total fixed assets, were allocated to specific sectors according to the description provided in Table 7.1B. The remaining undistributed government fixed assets totaling $1.9 trillion were allocated to IO sector 44, Public administration and defense.

The employment by sector in both U.S. technology matrices is the same, based on BLS Occupational Employment Statistics (OES) by 3-digit Standard Industrial Classification code for the year 2000 at http://www.bls.gov/oes/home.htm . Employment by SIC industry was converted to the IO ISIC using a concordance published by the United Nations Statistics Division. Since the OES data does not include self-employment, I used the ILO Table 1.C for the U.S. to adjust for self-employment using the 14 broad sectors reported there.

The aggregate capital stock for all other countries in the sample except Taiwan was constructed using two time series from United Nations *National Income Accounts* at http://unstats.un.org/unsd/nationalaccount/ :1) the local currency value of GDP at constant 1990 prices and 2) Gross fixed capital formation as a share of GDP. I used the OECD IO data for GDP in the most current year, and then imputed GDP in earlier years based on the real growth rate of GDP inferred from UN GDP. Next, I use the annual share of investment in GDP to impute an real investment series to 1970. I estimate an initial capital stock in 1970 by $K_{1970} = \frac{I_{1970}}{g+\delta}$, where I_{1970} is real investment in 1970, g is the geometric rate of growth of investment inferred from the subsequent 20 years of real investment, and δ is the rate of depreciation. I then use the standard perpetual inventory method to determine the capital stock in the current year. The depreciation rate of 0.037 was chosen so that the perpetual inventory capital stock estimate using UN NIPA data for the United States matched the capital stock estimate of the United States Bureau of Economic Analysis (BEA) for the year 2000. This rate of depreciation is low compared to that used in many studies; for example, Caselli and Feyrer (2007) use $\delta = 0.06$. However, for this study the BEA capital stock by sector gives an important check for the U.S. technology matrix, and this choice seems no more arbitrary than others used in the literature.

Russia and Slovakia only report time series data from 1990 and the imputed rate of growth of investment for the subsequent 10 years was negative for both countries. I therefore estimated their initial capital stock by $K_{1990} = \frac{I_{1990}}{\delta}$. The United Nations does not report data on Taiwan, so I used Penn World Table Version 6.2 (PWT) data for Taiwan's growth of real GDP and investment share of GDP. To adjust for local prices, Taiwan's rental rate computed with PWT data was multiplied by the ratio of the price level of GDP to the price level of investment from PWT.