International Productivity and Factor Price Comparisons

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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 to 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.

Keywords: factor-specific productivity; TFP differences; factor payments

JEL CLASSIFICATION: F16, J24, J31, O15

1. Introduction

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] Several different approaches in economic literature have evolved to explain these disparities. The Heckscher-Ohlin-Vanek (HOV) theory of international trade, rooted in the notion of similar technologies but different endowments among trading nations, posits factor price equalization (FPE) as the expected outcome of international trade. Within this tradition there are still various explanations for the evident failure of FPE in face of increasing world trade. Schott (2003) shows that cones of diversification allow the price of labor-intensive goods to determine factor payments in developing countries, whereas capital abundant developed countries specialize in capital-intensive goods at different factor prices. Alternatively, factor-specific differences in productivity inherent in the factors themselves can explain differences in factor payments. Trefler (1993) substantiates productivity-adjusted FPE among a group of 33 countries in 1983.

A different tradition outside the international trade literature focuses on differences in aggregate production efficiency due mainly to differences in total factor productivity (TFP). The best known examples are Hall and Jones (1999) and the extensive work of Parente and Prescott summarized in Parente and Prescott (2000). To put it simply, this tradition argues - without reference to trade or international prices - that some countries have low wages because they produce less goods, and they produce less goods because of broad features of their economic institutions and policies that can be measured only indirectly through TFP. This view thus emphasizes economy-wide differences in TFP as the primary source of differences in factor

[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.

payments in keeping with the notion that a migrant worker will earn more in a productive economy.

Another long- standing and influential view in the literature of economic development sees aggregate increases in labor productivity as a reflection of structural transformation away from backward, low productivity agriculture towards modern capital-intensive manufacturing. Lewis (1954) most famously espoused the notion of redundant labor in agriculture, and more recently Gollin et al. (2004) show that the relative output per worker in agriculture compared to non-agriculture production among development late-comers is not only low, it is significantly lower than that experienced during the past structural transformation of today's industrial nations. Many of today's low income countries - China is most noteworthy - continue to employ a large share of their labor force in relatively backward labor-intensive agricultural production in spite of rapid growth in exports of manufactured products.

This paper pulls together strands from these differing traditions to explain the specific pattern of factor payments in the context of countries at very different levels of economic development which engage in a substantial amount of international trade. I begin in the footsteps of Trefler (1993) by generating factor-specific measures of productivity to compare to factor prices. These measures of productivity are derived from data on country endowments and production by sector, together with a detailed technology matrix for the United States. I show that differences in factor-specific productivity are strongly correlated with the pattern of wages and rental rates but do not support a strict interpretation of productivity–adjusted FPE. I also find that many low income countries with low labor productivity also have relatively high capital productivity.[2]

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

To explain these findings I appeal to variations in total factor productivity (TFP) among nations, but in keeping with the notion of structural transformation I argue that these variations also depend to some degree on the type of economic activity. Within a multi-sector trade framework with exogenous international prices, I argue that sector-specific variations in TFP can explain the observed pattern of factor payments. If technological progress is uneven in the sense that some sectors 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, economy-wide usage of these factors will be correspondingly lower, and imputed productivities higher.

This paper contributes to a growing theoretical and empirical literature devoted to explaining and measuring TFP. The challenge for this literature is to explain continued large differences in output per worker in a world of growing international connections. I emphasize the importance of a disaggregated approach to studying TFP differences and I also present evidence against a Cobb-Douglas production function at the sectoral level. While I do not attempt to explain the source of sectoral differences in TFP, I draw on a large literature that recognizes inherently different features of production in broad sectors such as agriculture, industry, and services. Baumol (1967) was perhaps the first to argue that labor-intensive services were unlikely to experience the same level of productivity gains as modern industries. Rogerson (2008) shows that differences in demand and supply across broad sectors can help explain labor allocation differences among industrialized economies; Duarte and Restuccia (2010) apply a similar framework to a larger group of countries to verify the importance of different sectoral growth rates in aggregate productivity growth.

This paper also contributes to the literature on the measurement of factor payment shares among diverse countries. Gollin (2002) argues 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. I develop a correction that takes into account significant variations in self employment by sector. 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. Again using value-added by sector, I show that this correction is unwarranted by the data.

The rest of the paper is organized as follows: Section 2 presents the details of these adjustments to value-added and the resulting factor payment measures. Section 3 presents the factor-specific measures of productivity and compares them to the computed factor payments. In Section 4, I present a framework of uneven technological progress and some empirical support for this view, followed by a brief concluding section.

2. 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 outputs 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 total labor force, and the 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 also 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

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

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, GDP per worker and labor share exhibit a positive correlation, illustrated in Figure 1. The aggregate national income account data appears to conceal significant 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	47,734	0.55	0.66	0.66
Austria	2000	AUT	52,883	0.59	0.68	0.64
Belgium	2000	BEL	60,130	0.58	0.69	0.68
Brazil	2000	BRA	15,394	0.45	0.72	0.55
Canada	2000	CAN	54,623	0.64	0.76	0.73
China	2000	CHN	3,939	0.63	-	-
Czech Republic	2000	CZE	27,823	0.47	0.57	0.57
Denmark	2000	DNK	51,236	0.61	0.67	0.66
Finland	2000	FIN	43,902	0.54	0.63	0.61
France	2000	FRA	59,716	0.61	0.68	0.67
Germany	2000	DEU	53,421	0.61	0.68	0.67
Greece	1999	GRC	38,095	0.38	0.63	0.54
Hungary	2000	HUN	26,300	0.52	0.60	0.60
Indonesia	2000	IDN	5,408	0.32	0.97	0.65
Ireland	1998	IRL	49,918	0.47	0.58	0.55
Israel	1995	ISR	53,359	0.63	0.78	0.73
Italy	2000	ITA	58,697	0.46	0.63	0.62
Japan	2000	JPN	48,446	0.63	0.76	0.69
Korea	2000	KOR	33,718	0.49	0.78	0.65
Netherlands	2000	NLD	54,762	0.58	0.65	0.64
New Zealand	1995/96	NZL	38,068	0.48	0.61	0.60
Norway	2001	NOR	70,840	0.50	0.54	0.54
Poland	2000	POL	21,406	0.49	0.66	0.57
Portugal	1999	PRT	28,890	0.56	0.75	0.68
Russia	2000	RUS	15,972	0.35	0.38	0.37
Slovak Republic	2000	SVK	22,842	0.46	0.51	0.52
Spain	2000	ESP	46,961	0.56	0.69	0.66
Sweden	2000	SWE	50,440	0.66	0.73	0.71
Switzerland	2001	CHE	56,217	0.67	-	-
Taiwan	2001	TWN	44,156	0.61	-	-
Turkey	1998	TUR	17,815	0.25	0.57	0.43
United Kingdom	2000	GBR	49,516	0.65	0.73	0.72
USA	2000	USA	70,393	0.63	0.68	0.67
Correlation with GDP per worker (excluding 3 countries with no self-employment data)				0.71	0.03	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.C. 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.

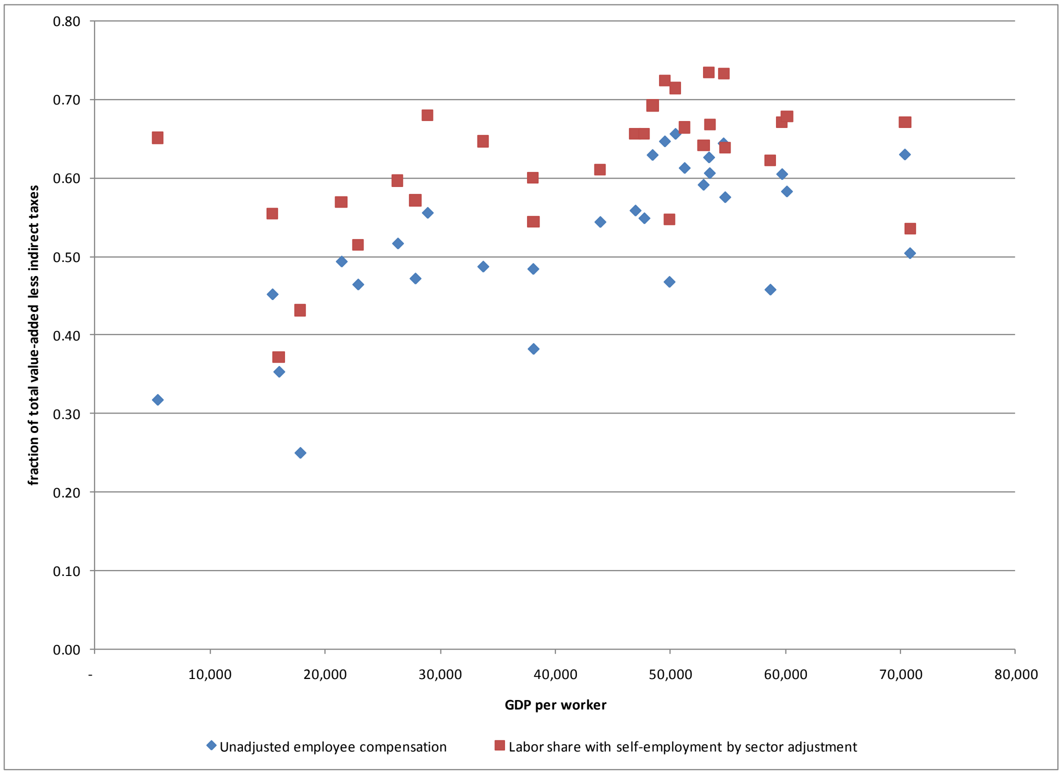

Fig. 1. Share of unadjusted employee compensation compared to labor share with self-employment adjustment by sector.

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 of agriculture compared to that in agriculture. I return to this topic below and show how uneven technological progress influences the measurement of economy-wide factor productivity.

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	0.87	4.20	0.67
Brazil	0.21	0.72	2.92	0.37
Russia	0.10	0.35	1.44	0.07
Turkey	0.43	0.93	4.88	0.56
Poland	0.17	0.89	5.00	0.25
Slovak Republic	0.06	0.07	1.12	0.10
Hungary	0.05	0.35	1.22	0.14
Czech Republic	0.05	0.34	1.28	0.17
Portugal	0.12	0.85	3.48	0.26
Korea	0.11	0.92	2.73	0.38
New Zealand	0.10	0.61	1.40	0.21
Greece	0.16	0.95	2.17	0.40
Finland	0.06	0.68	1.25	0.14
Spain	0.07	0.49	2.02	0.19
Australia	0.05	0.54	1.47	0.17
Japan	0.05	0.87	2.89	0.17
United Kingdom	0.02	0.48	1.46	0.12
Ireland	0.09	0.80	1.62	0.19
Sweden	0.02	0.63	1.16	0.10
Denmark	0.03	0.51	1.25	0.08
Austria	0.06	0.83	2.35	0.13
Israel	0.03	0.62	1.59	0.20
Germany	0.03	0.48	2.09	0.11
Canada	0.03	0.54	1.56	0.16
Netherlands	0.03	0.51	1.27	0.11
Switzerland	0.04	-	3.06	-
Italy	0.06	0.55	1.91	0.27
France	0.04	0.70	1.37	0.11
Belgium	0.02	0.77	1.24	0.16
USA	0.03	0.36	2.01	0.07
Norway	0.04	0.62	1.76	0.07

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.[3] 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 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.[4] There are several possible explanations for this discrepancy: the

[3] 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).

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

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 $1-\alpha_L$.

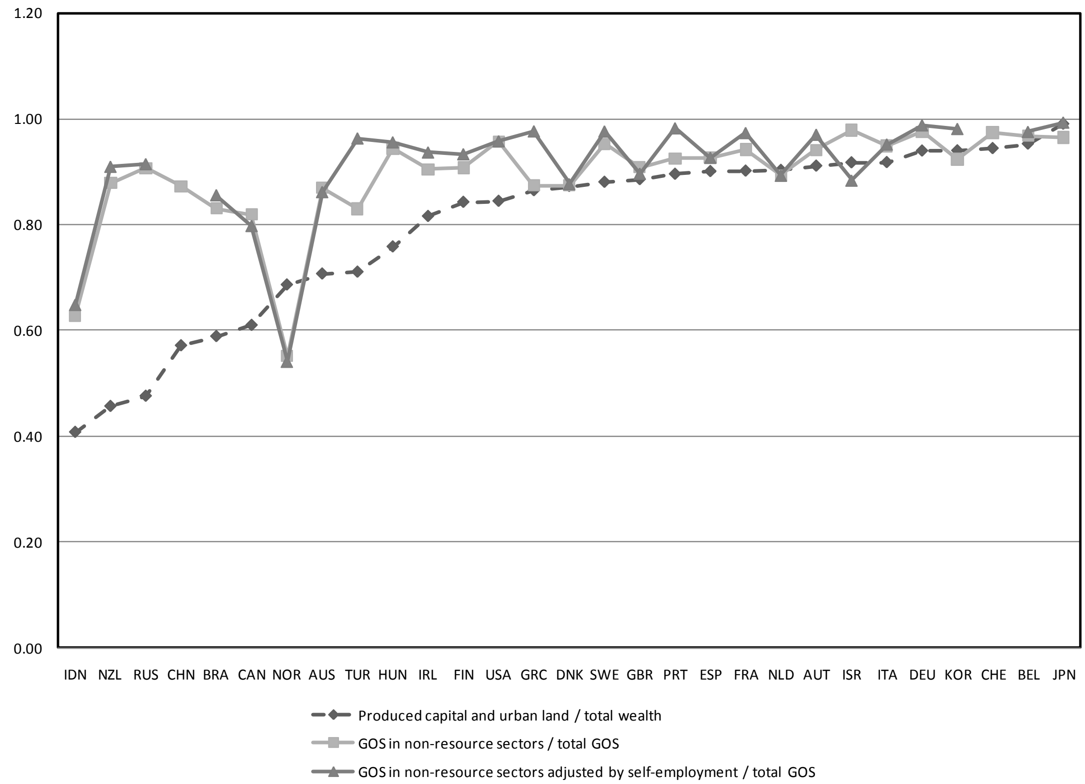

Fig. 2. World Bank (2006) estimate of produced capital and urban land as share of total wealth in the year 2000 compared to share of gross operating surplus (GOS) from non-resource intensive sectors to total GOS.

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 to rental ratio seems surprisingly diverse. Thirteen countries have a wage to rental ratio above that of the United States. Nineteen countries have relatively low wages but relatively high rental rates and so have substantially lower wage to 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 HOV 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 to rental ratios.

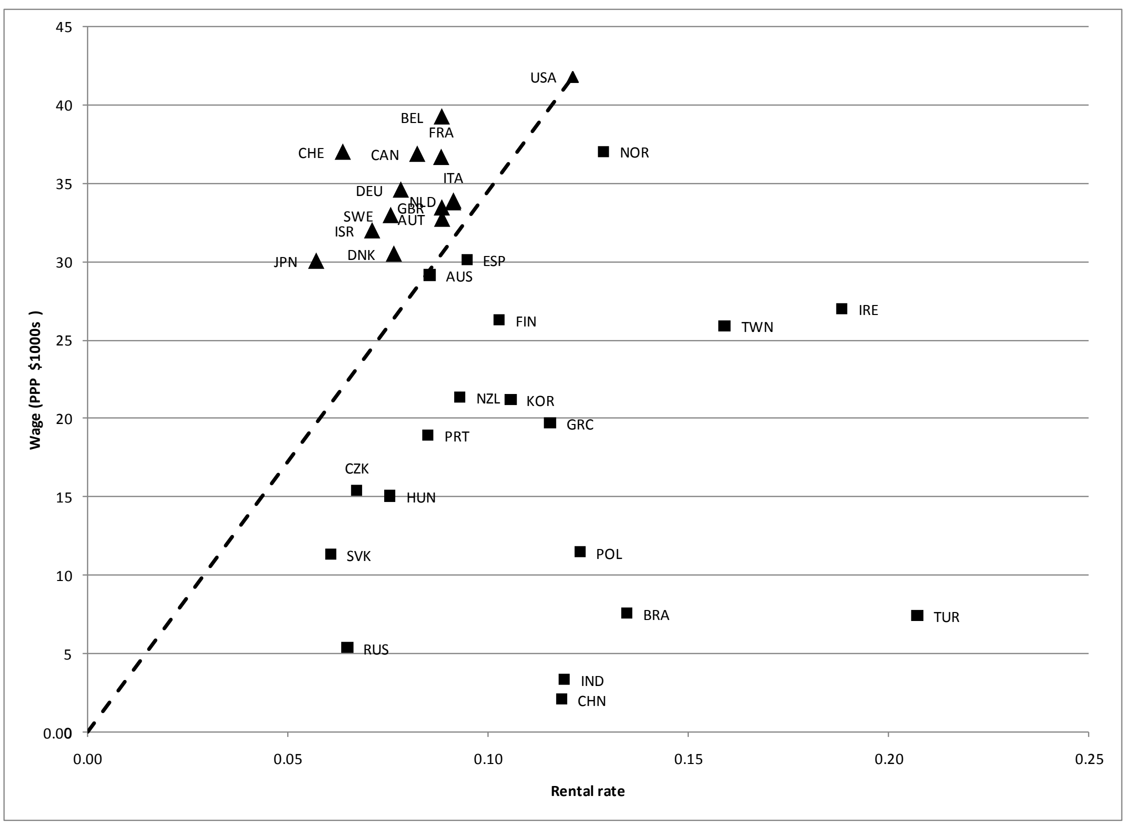

Fig. 3. Average factor payments for labor and capital across countries in the year 2000

3. Measuring 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, denoted simply by π_{fd}.

I propose a simple measure of π_{fd} that both allows for productivity variations between sectors and can be measured with only the reference country's technology matrix, given data on the $f \times 1$ endowment vector, v_d, and the $n \times 1$ output vector y_d for country d. Define the virtual endowment $\tilde{\mathrm{v}}_d$ as the vector of factors that would be used by the reference country to produce country d's output, so that $\tilde{\mathrm{v}}_d = \mathrm{A}_c \mathrm{y}_d$. The factor-specific productivity can then be computed by $\tilde{\pi}_{fd} = {}^{\tilde{v}_{fd}}\!\big/_{v_{fd}}$, where $\tilde{v}_{fd}$ and v_{fd} are the f^{th} elements in the respective endowments vectors. Let $\tilde{\Pi}_d$ be the f by f diagonal matrix of $\tilde{\pi}_{fd}$ with zero elements in the off-diagonals.

The factor-specific productivity measure constructed in this fashion is a weighted average of the differences in factor usage across sectors between the reference country and comparison countries. The weights are the shares of total factors used (directly and indirectly) in country d's

$i'th$ industry.[5] If the difference in factor usage is uniform across sectors, the weighted average will correspond to the factor-specific-productivity differences suggested by Trefler (1993). Only in this special case will $\tilde{\Pi}_d \mathrm{A}_d = \mathrm{A}_c$. In the more general case that industries vary in their use of factors across countries, then $\tilde{\Pi}_d \mathrm{A}_d \neq \mathrm{A}_c$, although by construction $\tilde{\Pi}_d \mathrm{A}_d \mathrm{y}_d \equiv \mathrm{A}_c \mathrm{y}_d$.

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.[6] 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.

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[5] Note that $\dfrac{\tilde{v}_{fd}}{v_{fd}} = \dfrac{\sum_{i=1}^{n} \pi_{fid} a_{fid} y_{id}}{\sum_{i=1}^{n} a_{fid} y_{id}}$ under the full employment assumption that $v_{fd} = \sum_{i=1}^{n} a_{fid} y_{id}$, and thus the $i'th$ term in this summation can be written as $\varpi_{fi} \pi_{fid}$ where $\varpi_{fi} = \dfrac{a_{fid} y_{id}}{\sum_{i=1}^{n} a_{fid} y_{id}}$.

[6] Although the BEA goes to great pains to estimate fixed assets by sectors, the United States industry classification differs from the international standard ISIC, so it was problematic to match the sector-based capital to the same sectors as the OECD input-output data. However, I used the BEA values for a benchmark total capital for the United States, about 27 trillion U.S. dollars, to infer the economy-wide rate of return used in turn to compute sector-specific capital.

If productivity differences are uniform across industries there is a clear and simple relationship between factor-specific productivity and factor payments. The assumption of zero profits and exogenous world prices p implies that $\mathrm{p} = \mathrm{A}_d^T \mathrm{w}_d$, where w_d is the factor payment vector for country d. This in turn implies that $\mathrm{A}_c^{\mathrm{T}} \mathrm{w}_c = \mathrm{A}_d^{\mathrm{T}} \mathrm{w}_d$, where A_c is the U.S. Leontief matrix and w_c is the U.S. factor payment vector. If $\tilde{\Pi}_d \mathrm{A}_d = \mathrm{A}_c$, then $\mathrm{A}_d^T \mathrm{w}_d = \mathrm{A}_d^T \tilde{\Pi}_d \mathrm{w}_c$, so that $\mathrm{w}_d = \tilde{\Pi}_d \mathrm{w}_c$.[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):

$$\begin{array}{llll} \log(w_{Ld}) = & 3.74 + & 1.15 \log(\pi_{Ld}), & \\ \text{(s.e.)} & (0.03) & (0.04) & R^2 = 0.97 \\ \log(w_{Kd}) = & -2.14 + & 0.74 \log(\pi_{Kd}), & \\ & (0.05) & (0.11) & R^2 = 0.59 \end{array}$$

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 [1.15, 1.19] and on $\log(\pi_{Kd})$ of [0.74, 1.25]. Hence one can reject the hypothesis that productivity-adjusted factor price

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

equalization holds for labor, and although the probability limit for the coefficient on capital productivity includes 1, it is estimated with much less precision. 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. 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.

The results also indicate that the productivity of capital has no correlation with the productivity of labor, in general accord with the observed wage to rental ratios, and hence cannot stem from economy-wide differences in industriousness and technology. There is however a distinctive pattern in the prediction error between productivity and factor payments clearly visible in Figure 4: those countries with low wage to 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 to 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 to rental country groups.

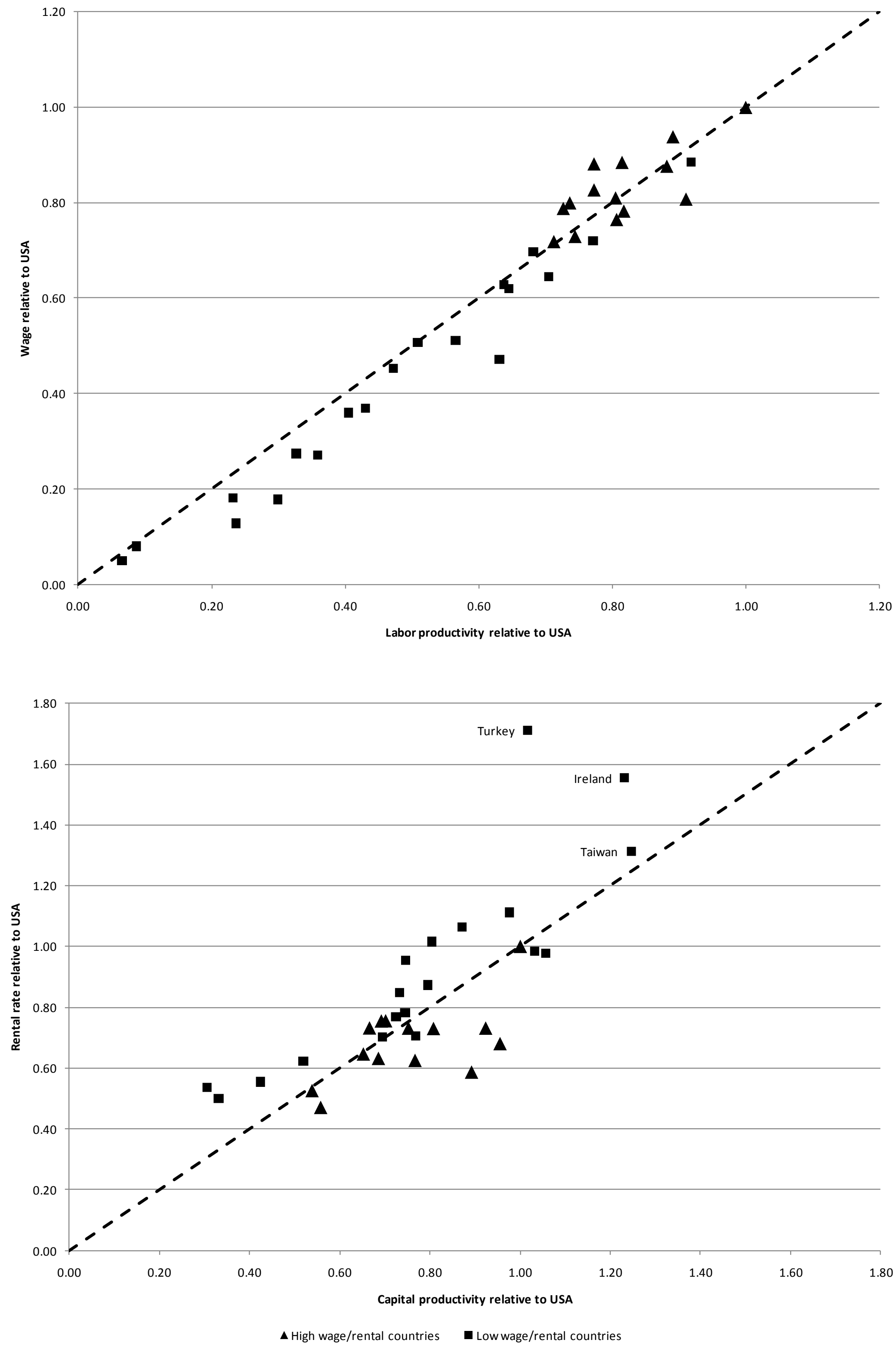

Fig. 4. Factor payments and factor productivity

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

To motivate my empirical analysis, I 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:

$$1 = \theta_{id} \left[\delta_i a_{Lid}^{\sigma-1/\sigma} + (1-\delta_i) a_{Kid}^{\sigma-1/\sigma} \right]^{\sigma/\sigma-1} \tag{2}$$

where δ_i is the distribution share of labor in industry i, θ_{id} is total factor productivity in industry i relative to the reference country c, and σ is the constant elasticity of substitution between factors, assumed to be the same across industries. I further 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 unit factor input requirements for labor (a_{Lid}) and capital (a_{Kid}) are determined by profit maximization given exogenous world prices. Industry 1 represents a labor-intensive sector, such as agriculture, and industry 2 represents a capital-intensive sector, such as manufacturing. Finally, I assume both countries produce and trade both goods at the exogenously determined world price.

The standard profit maximization assumptions used to derive the unit factor demand leads to a comparison of input coefficients between two countries in industry i given by:

$$\frac{a_{fic}}{a_{fid}} = \left(\frac{w_{fd}}{w_{fc}} \right)^{\sigma} \theta_{1d}^{\ 1-\sigma} . \tag{3}$$

Equation (3) shows that differences in factor usage in the special Cobb-Douglas case where $\sigma = 1$ will be industry-neutral. 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

$$\mathrm{A}_c = \begin{bmatrix} \dfrac{w_{Ld}}{w_{Lc}} & 0 \\ 0 & \dfrac{w_{Kd}}{w_{Kc}} \end{bmatrix} \mathrm{A}_d \, . \tag{4}$$

In the general equilibrium setting, the sector-specific differences in total factor productivity will determine the differences in factor payments. 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. In this special case, the virtual endowment measure of factor-specific productivities, $\tilde{\Pi}_d$, will be equal to the above diagonal matrix of relative factor payments. Under the assumption of zero profits and exogenous world prices p, $\mathrm{w}_c = \tilde{\Pi}_d^{\;-1} \mathrm{w}_d$. In other words, productivity-adjusted factor price equalization should hold in the special Cobb-Douglas case of industry-based differences in total factor productivity.

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 reference country c, 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 labor-intensive sector is relatively more backward than the capital-intensive sector, the country will be represented by point d, and the wage to rental ratio will be below that in the high wage country. The effect is exactly 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, the use of less capital be used in production in both industries in comparison to the high wage country would be interpreted as a higher productivity of capital.

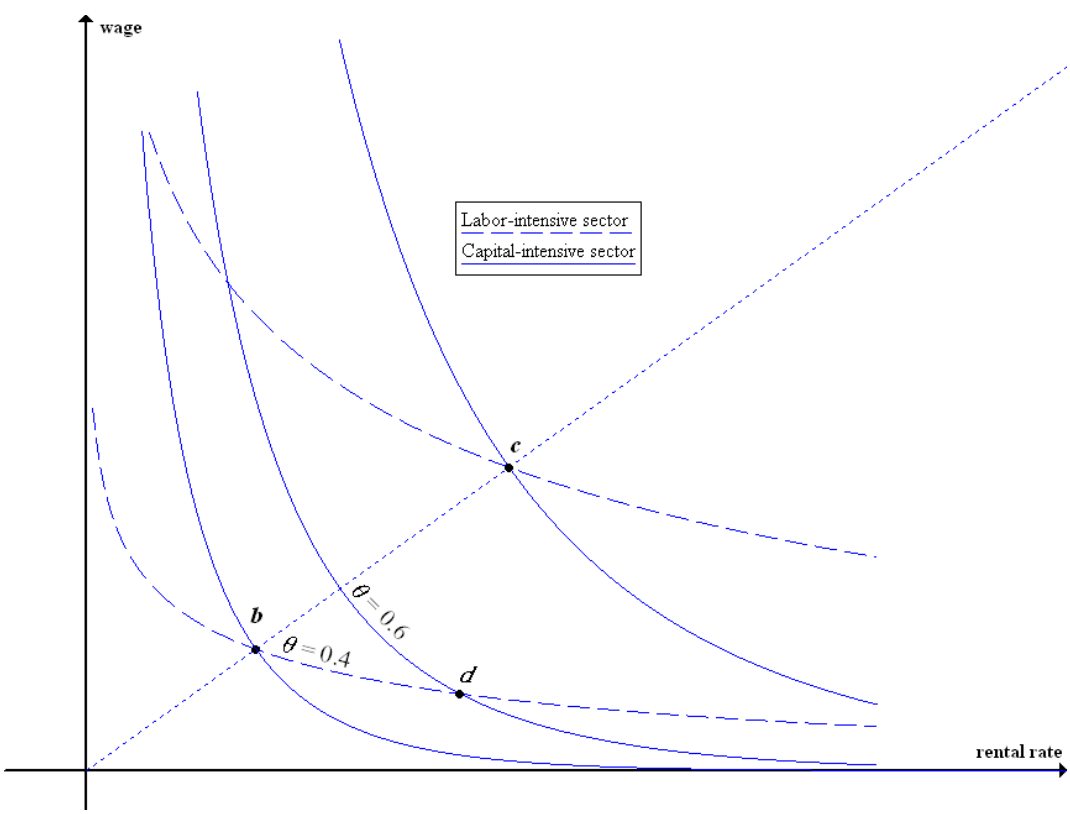

Fig. 5. Uneven technological development in a two-sector model, drawn with CES isocost curves and σ = 0.9.

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

$$\mathrm{A}_c = \begin{bmatrix} \left(\frac{w_{Ld}}{w_{Lc}}\right)^{\sigma} \theta_{1d}^{1-\sigma} a_{L1d} & \left(\frac{w_{Ld}}{w_{Lc}}\right)^{\sigma} \theta_{2d}^{1-\sigma} a_{L2d} \\ \left(\frac{w_{Kd}}{w_{Kc}}\right)^{\sigma} \theta_{1d}^{1-\sigma} a_{K1d} & \left(\frac{w_{Kd}}{w_{Kc}}\right)^{\sigma} \theta_{2d}^{1-\sigma} a_{K2d} \end{bmatrix} = \begin{bmatrix} \left(\frac{w_{Ld}}{w_{Lc}}\right)^{\sigma} & 0 \\ 0 & \left(\frac{w_{Kd}}{w_{Kc}}\right)^{\sigma} \end{bmatrix} \mathrm{A}_d \begin{bmatrix} \theta_{1d}^{1-\sigma} & 0 \\ 0 & \theta_{2d}^{1-\sigma} \end{bmatrix}. \quad (5)$$

The relationship between wages in the two countries can no longer be summarized by a single diagonal matrix. 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

$$\tilde{\Pi}_d = \begin{bmatrix} \hat{\theta}_d \left(\frac{w_{Ld}}{w_{Lc}}\right)^{\sigma} & 0 \\ 0 & \hat{\theta}_d \left(\frac{w_{Kd}}{w_{Kc}}\right)^{\sigma} \end{bmatrix} \quad (6)$$

where $\hat{\theta}_d$ is a weighted average of $\theta_{1d}^{1-\sigma}$ and $\theta_{2d}^{1-\sigma}$.[8] This productivity measure will no longer equal the relative factor payments, but it is easy to show that $\tilde{\pi}_{Ld} > \frac{w_{Ld}}{w_{Lc}}$ and $\tilde{\pi}_{Kd} < \frac{w_{Kd}}{w_{Kc}}$ as long as TFP is higher in the capital-intensive sector, so that the productivity measure has a predictable

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[8] This generalizes easily to the f by n case. The typical diagonal element of $\tilde{\Pi}_d$ is equal to $\left(\frac{w_{fd}}{w_{fc}}\right)^{\sigma} \sum_{i=1}^{n} \theta_{idc}^{1-\sigma} \varpi_{fi}$ 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, $0 < \varpi_{fi} < 1$.

bias. If a country has higher TFP in the labor-intensive sector and thus has a higher relative wage-rental ratio than country, the direction of these biases in the virtual endowment productivity measures will be reversed. In the multi-sector case, the same bias occurs in the low wage to rental country as long as the sector with the lowest TFP has a lower labor distribution parameter (δ_i) than the sector with the highest TFP.[9]

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 to 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 to rental ratio. The results, presented in Table 3, show a highly significant success rate for both factors. Industry variations in TFP together with less than unitary substitution between labor and capital can explain the failure of

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[9] For the low wage rental country where $n > 2$, let sector 1 be the sector with the lowest TFP (measured by θ_1) and sector 2 the sector with the highest TFP (measured by θ_2). The cost-minimizing solution to the CES system must satisfy $\begin{bmatrix} \delta_1^\sigma & (1-\delta_1)^\sigma \\ \delta_2^\sigma & (1-\delta_2)^\sigma \end{bmatrix} \begin{bmatrix} w_{Lc}^{1-\sigma} \\ w_{Kc}^{1-\sigma} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ for the reference country c (where I have normalized all prices to be 1 as is the convention in input-output accounting), and $\begin{bmatrix} \delta_1^\sigma & (1-\delta_1)^\sigma \\ \delta_2^\sigma & (1-\delta_2)^\sigma \end{bmatrix} \begin{bmatrix} w_{Ld}^{1-\sigma} \\ w_{Kd}^{1-\sigma} \end{bmatrix} = \begin{bmatrix} \theta_{1d}^{1-\sigma} \\ \theta_{2d}^{1-\sigma} \end{bmatrix}$ for the comparison country d. Solving both linear systems and taking the factor payment ratios across countries gives 1) $\left(\frac{w_{Ld}}{w_{Lc}}\right)^{1-\sigma} = \frac{(1-\delta_2)^\sigma \theta_{1d}^{1-\sigma} - (1-\delta_1)^\sigma \theta_{2d}^{1-\sigma}}{(1-\delta_2)^\sigma - (1-\delta_1)^\sigma}$ and 2) $\left(\frac{w_{Kd}}{w_{Kc}}\right)^{1-\sigma} = \frac{-\delta_2{}^\sigma \theta_{1d}^{1-\sigma} + \delta_1^\sigma \theta_{2d}^{1-\sigma}}{-\delta_2{}^\sigma + \delta_1^\sigma}$. I want to prove that $\tilde{\pi}_{Ld} = \hat{\theta}_d \left(\frac{w_{Ld}}{w_{Lc}}\right)^\sigma > \frac{w_{Ld}}{w_{Lc}} \Rightarrow \left(\frac{w_{Ld}}{w_{Lc}}\right)^{1-\sigma} < \hat{\theta}_d$, where $\hat{\theta}_d$ is a weighted average of $\theta_i^{1-\sigma}$ for all sectors in country d. It is sufficient to prove that $\left(\frac{w_{Ld}}{w_{Lc}}\right)^{1-\sigma} < \theta_1^{1-\sigma}$.This will be the case as long as $\delta_1 > \delta_2$, which assures that both denominators in the right hand sides of 1) and 2) are positive. Analogous reasoning shows that $\tilde{\pi}_{Kd} = \hat{\theta}_d \left(\frac{w_{Kd}}{w_{Kc}}\right)^\sigma < \frac{w_{Kd}}{w_{Kc}}$, and the reverse biases hold for high wage rental countries where $\theta_1 > \theta_2$.

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.

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	Capital Productivty	Rental Rate	Sign test of prediction error
Countries with High Wage Rental Ratios						
Austria	0.82	0.78	0	0.67	0.73	0
Belgium	0.89	0.94	1	0.75	0.73	1
Canada	0.77	0.88	1	0.96	0.68	1
Denmark	0.74	0.73	0	0.69	0.63	1
France	0.88	0.88	0	0.81	0.73	1
Germany	0.77	0.83	1	0.65	0.65	1
Israel	0.81	0.77	0	0.89	0.59	1
Italy	0.91	0.81	0	0.69	0.75	0
Japan	0.71	0.72	1	0.56	0.47	1
Netherlands	0.80	0.81	1	0.70	0.76	0
Sweden	0.73	0.79	1	0.77	0.63	1
Switzerland	0.81	0.88	1	0.54	0.53	1
United Kingdom	0.74	0.80	1	0.92	0.73	1
Countries with Low Wage Rental Ratios						
Australia	0.68	0.70	0	0.77	0.71	0
Brazil	0.23	0.18	1	0.98	1.11	1
China	0.07	0.05	1	1.06	0.98	0
Czech Republic	0.43	0.37	1	0.42	0.55	1
Finland	0.64	0.63	1	0.73	0.85	1
Greece	0.63	0.47	1	0.75	0.95	1
Hungary	0.41	0.36	1	0.52	0.62	1
Indonesia	0.09	0.08	1	1.03	0.98	0
Ireland	0.70	0.65	1	1.23	1.56	1
Korea, Republic o	0.51	0.51	1	0.80	0.87	1
New Zealand	0.57	0.51	1	0.72	0.77	1
Norway	0.92	0.89	1	0.87	1.06	1
Poland	0.33	0.27	1	0.80	1.02	1
Portugal	0.47	0.45	1	0.70	0.70	1
Russian Federatio	0.24	0.13	1	0.31	0.54	1
Slovakia	0.36	0.27	1	0.33	0.50	1
Spain	0.77	0.72	1	0.75	0.78	1
Taiwan	0.65	0.62	1	1.25	1.31	1
Turkey	0.30	0.18	1	1.02	1.71	1
Total Correct predictions			26			26
Binomial probability, n=32			< 0.001			< 0.001

4.1. Further empirical evaluation of technology differences between countries

The pattern of international differences in technology matrices generated by the simple CES production function in Equation (2) allows for different factor payment shares but still implies the same ranking of industries by factor intensity across countries. I have also argued that a specific pattern of cross-country variations in TFP between labor and capital-intensive industries explains the relation of measured factor productivities to factor payments among this diverse group of 33 economies. Here I examine further evidence for these assertions by constructing separate technology matrices for most of the countries in the sample using more aggregated data, and then using these technology matrices to measure TFP by sector.

The International Labor Office publishes labor data by sector at a fourteen sector level of aggregation for most of the countries in the sample which was used in the computation of self-employment shares in Table 1 above. I infer capital use by sector from the value-added payments to capital, adjusted for self-employment as described above, divided by the economy-wide rental rate. I combine the OECD input-output data, aggregated in a conforming manner, with direct capital and labor inputs by 14 sectors to construct each country's 2 by 14 technology matrix A of direct and indirect unit inputs of capital (a_{Ki}) and labor (a_{Li}). This in turn allows me to determine a fourteen sector ranking by capital intensity which appears to be fairly consistent across all countries.[10]. Table 4 presents the resulting ranking from low to high capital-intensive according to ISIC revision 3 sectors, together with 4 countries' TFP by sector described below. I further divide the sectors into two categories, the labor-intensive sector and the capital-

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[10] I first rank each individual country's sectors from low to high capital intensity according to a_{Ki}/a_{Li}. I then take the mode of these individual rankings, and where there are tied sectors by mode I rank them by the simple average of rankings across countries. All countries were then compared to the derived international ranking using Spearman's rank correlation statistic. The null hypothesis of no correlation between individual countries and the international ranking was rejected at the 0.025 percent level of significance for all countries.

intensive sector. Basic services such as hotels and restaurants are included in the labor-intensive or traditional sector, and utilities and mining are included in the capital-intensive modern sector.

To measure TFP by sector 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. 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 $\mathrm{A_c}$ 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 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). The TFP for industry i of country d relative to country c (suppressing the industry subscript for clarity) is given by:

$$TFP_{dc} = \left(\frac{\bar{a}_L}{a_{Ld}}\right)^{\alpha_d} \left(\frac{\bar{a}_K}{a_{Kd}}\right)^{1-\alpha_d} \left(\frac{a_{Lc}}{\bar{a}_L}\right)^{\alpha_c} \left(\frac{a_{Kc}}{\bar{a}_K}\right)^{1-\alpha_c} \qquad (7)$$

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 to rental ratios, China and Brazil, and two large countries with very high wage to rental ratios, Japan and France.

TABLE 4

TFP for selected countries by sectors ranked from low to high capital intensity

Labor intensive sectors	Brazil	China	France	Japan
Education (M)	23	21	101	86
Health (N)	17	18	69	76
Agriculture (A, B)	40	13	134	78
Hotels and restaurants (H)	38	22	132	101
Public administration (L)	58	18	99	74
Other services (O, P, Q)	9	18	48	45
Wholesale and retail trade (G)	22	18	82	66
Capital intensive sectors				
Construction (F)	39	18	85	64
Manufacturing (D)	41	24	87	58
Transport and communications (I)	35	25	74	74
Financial Intermediation (J)	50	29	81	47
Real estate (K)	52	36	80	50
Utilities (E)	84	54	93	50
Mining (C)	62	40	86	27
Average TFP for labor intensive sectors	30	18	95	75
Average TFP for capital intensive sectors	52	32	84	53

The computations confirm a wide range of TFP between the broad industry groups, and the pattern in the reported countries appears to accord with the argument that TFP will be higher in capital-intensive industries in low wage to rental countries. To evaluate more systematically how TFP varies between labor-intensive and capital-intensive industries across all countries (except the reference country) , I estimate a simple regression with the natural log of TFP_{ic} (in industry i, country c) as the dependent variable, and the variation in TFP modeled by a constant term, country fixed effects (not reported), and two dummy variables to compare the capital-intensive sectors in the 13 high wage to rental countries (hkd) and the 19 low wage rental countries (lkd):

$$\begin{array}{l} \text{Log}(\text{TFP}_{ic}) = -0.724 + [\,\textit{fixed effects for}\ 32\ \textit{countries}\,] - 0.128\ (\text{hkd}) + 0.127\,(\text{lkd})\ + \varepsilon_{ic} \\ \quad (\text{s.e.}) \qquad (0.072) \qquad\qquad\qquad\qquad\qquad\qquad\qquad (0.039) \qquad\quad (0.033)\ \ \text{R}^2 = 0.72 \end{array} \tag{8}$$

Both dummy variables have the predicted sign and both are significant at the 0.01 percent level. The results indicate that TFP is about 13 percent lower on average in capital-intensive industries compared to labor-intensive industries among high wage to rental countries, whereas in low wage to rental countries TFP is about 13 percent *higher* in capital-intensive industries compared to labor-intensive industries.

So far I have maintained the strong assumption that all goods are traded, but many studies (*e.g.* Davis and Weinstein, 2003) document the significance of non-traded goods in international comparisons of technology. In this view, factor prices are determined by the traded goods sectors, and to the extent that FPE fails, the price of non-traded goods reflects the differing factor prices in each country. Typically, non-traded goods are assumed to be labor-intensive, so that they will thus be relatively cheap in low wage countries but relatively expensive in high wage countries. In my framework these price differences would be captured by differences in TFP, and so the imputed sector specific differences in TFP may in fact be due in part or entirely to unmeasured price differences.

In the absence of better producer price indexes by sector for the sample countries, I present a simple evaluation of this alternative hypothesis by repeating the regression above for a subset of traded goods sectors.[11] I identify non-traded goods on the basis of exports and imports

[11] In his careful study of TFP differences within manufacturing industries across 10 OECD countries, Harrigan (1999) uses a separate deflator for machinery and equipment only. As Duarte and Restuccia (2010) note, disaggregated PPP deflators are based on the GDP expenditure breakdown rather than producer prices.

by sector in the input-output data. The data show that 4 sectors can clearly be defined as non-traded: public administration, health, construction, and education.[12] I simply drop these sectors from the sample and repeat regression (8) on the remaining ten traded industries, as indicated by TFP_{tc} (in traded industry t, country c):

$$\begin{array}{llll} \mathrm{Log}(\mathrm{TFP}_{tc}) = -0.723 + [\,\textit{fixed effects for } 32 \textit{ countries}\,] & -\,0.130(\mathrm{hkd}) & +\,0.191(\mathrm{lkd}) & +\ \varepsilon_{tc} \\ \text{(s.e.)} \qquad (0.09) & (0.049) & (0.042) & R^2 = 0.68 \end{array} \tag{9}$$

Here again the regression results substantiate a significant difference in the TFP of capital intensive industries across the two groups of countries within the subset of traded goods sectors.

This section presents a somewhat cursory look at the measurement of TFP using the OECD input-output tables also used to measure factor-specific productivity, combined with very basic measures of sector-specific inputs. I show that large differences in TFP across industries broadly substantiate a process of uneven development, and provide further evidence that countries' technology matrices embody industry-specific variations in production technology which can explain the observed relationship between factor productivity and factor payments. The TFP measures presented here also capture unmeasured variations in human capital and relative prices. However, the results are consistent with the recent work of Duarte and Restuccia (2010) who, after controlling for sectoral price differences in a model simulation, document extensively sectoral labor productivity differences between agriculture, services, and industry in a group 29 diverse economies.[13]

[12] The breakdown into traded and non-traded goods was based on a simple definition of trade by sector equal to exports plus imports divided by output by sector. Among the 14 sectors listed in Table 4, a natural break occurred between these 4 sectors (public administration, health, construction, and education), each with a median of trade across countries equal to 1 percent or less, and the next sector, utilities, with a median of trade equal to 10 percent and an average equal to 20 percent. The two sectors with the most trade were agriculture and manufacturing.

[13] In particular they note that "…differences in labor productivity levels between rich and poor coutnries are larger in agriculture and services than in manufacturing." (page 131), although they use the standard three-way sectoral

5. 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 can better explain these technology differences and the resulting pattern of international factor payments than differences inherent in factors or common across economies. Less than unitary factor substitutability helps explain high rental rates and low wages in low income countries in the presence of substantial international trade, beyond what would be predicted by comparisons of factor productivity.

Value-added data by sector permit me to examine carefully 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 to rental ratios that cannot be explained by a single industry-neutral productivity parameter, as is often employed in the HOV literature. Large differences in TFP measured in the aggregate across countries help

division based on World Bank data and not the capital intensive criteria that I have used here, and they do not assume common world prices.

explain the observed large variations in factor payments, but a more nuanced view of these variations that reflects a process of structural transformation can better explain international differences in factor payments.

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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 and employment by sector 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. 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.

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. Since there was no substantial difference between the results with either technology matrix, I report only those with the value-added technology matrix.

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 a 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.