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On the similarity of country endowments

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Abstract

We study the production side of the Heckscher–Ohlin model empirically. The evidence we present suggests that the endowments of countries around the world are too dissimilar for all countries to be able to produce the same set of goods. In contrast, the endowments of the rich OECD countries are sufficiently similar, so that these countries do not have to specialize in different subsets of goods. Our findings have implications for a variety of issues ranging from the trade and wages debate to economic development. Our analysis relies on the lens condition of Deardorff [Journal of International Economics 36 (1994) 167–175] that compares country endowments with sectoral factor inputs. We mainly focus on the production factors capital and labor. We test the robustness of the results with different data sets and with corrections for international differences in productivity and human capital. We confirm the similarity of the developed OECD countries with skilled and unskilled labor data. We also investigate in detail the implications of measurement error and sectoral aggregation.

Keywords: Heckscher–Ohlin; Multicone production; Factor price equalization

JEL classification: F1

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1. Introduction

The Heckscher–Ohlin (HO) theory primarily relies on differences in country endowments to explain the international pattern of trade and production. In its $2 \times 2 \times 2$ version, the capital-abundant country exports the capital-intensive good and the labor-abundant country the labor-intensive product. The model also generates a distinct pattern of specialization when countries have very different endowment ratios. With very different capital–labor ratios, the capital-abundant country abandons the production of the labor-intensive good entirely and/or the other country no longer produces the capital-intensive good. The HO theory provides a specific criterion to indicate when this type of specialization occurs. If country endowment ratios do not lie between the capital–labor ratios of both sectors, the endowments are said not to lie in the same diversification cone. In that case, countries will produce different goods. Otherwise, the endowments are similar enough to be inside the same cone and the two countries can produce the same products. In the present empirical study, we investigate whether the endowments are similar enough to allow countries to produce the same set of goods in the real world of multiple countries and sectors. We base our analysis on Deardorff's (1994) who extends the diversification cone condition to higher dimensions.

The question whether or not countries lie in the same cone of diversification has received increasing attention in recent years. Leamer (1996) for example studies Stolper–Samuelson effects in the US, motivated by the well-known theorem of international trade that relates price changes of domestically produced goods to domestic factor rewards. Leamer emphasizes that whether or not developed and developing countries lie inside the same cone has very different implications for the trade and wages debate. Consider a drop in the price of unskilled labor-intensive goods that developing countries export. If the US also produces these goods, the Stolper–Samuelson Theorem predicts a decline in the real wage of unskilled labor and a rise in that of skilled labor. In other words, the price changes should induce more wage inequality in the US. If the US and developing countries produce entirely different goods, however, unskilled labor should not fear competition from cheaper imports from developing countries at all. To the contrary, lower prices for consumers should increase the real wage of both skilled and unskilled labor.

The similarity of endowments has important implications also for economic development. In a one-sector neoclassical growth model, capital accumulation lowers a country's return to capital and its growth rate. This does not happen, however in a multi-sector HO model when countries lie in the same cone. This observation constitutes a critical component of the Ventura (1997) explanation of the sustained, rapid growth in East Asia. With factor price equalization, factor returns are determined at the world level, and an individual country's rapid capital accumulation does not lead to a drastic drop in its return to capital. As that country grows, it shifts its production towards more capital-intensive goods and it exports these goods at given international prices (Rybczynski effect).[1]

The literature is increasingly aware of the importance of the question addressed in this paper. Slaughter (1998) stresses the need to explore fully the implications of different cones for trade and wages. Deardorff (1998a,b) studies the consequences of different cones of diversification on economic growth and fragmentation of production. Feenstra and Hanson (1997) analyze US outsourcing to Mexico in a model that assumes the two countries lie in different cones. The cone question is also relevant for the factor content of trade studies. Trefler (1995) assumes one cone of diversification for the entire world. Davis and Weinstein (1998) on the other hand take a different cone for each and every OECD country. Our work provides a middle ground here: there are different cones, yet several countries can lie in one and the same cone. Despite this increasing attention to diversification cones, empirical work that directly addresses the issue is scarce. To our knowledge, only the research by Schott (2002) has tackled the cone question from an empirical point of view. Schott bases his analysis on Leamer (1987), whereas we follow Deardorff's (1994) theoretical work. Our findings are compatible, however: we both provide evidence that there is more than one cone of diversification.

The results that we present in this paper suggest that developed and developing countries do not lie in the same cone of diversification, while developed OECD countries do.[2] Due to data limitations we mostly focus on capital and labor. We verify the robustness of the results with various data sets and use various adjustment methods to correct for international productivity differences. For a limited group of OECD countries for which there are internationally comparable data, we extend the analysis to skilled and unskilled labor and confirm the similarity of the factor proportions of developed OECD countries. We also investigate the potential impact of sectoral aggregation and measurement error on our findings.

Note that our paper is not primarily a test of factor price equalization—it is evident that factor prices are different across countries.[3] We are primarily interested in whether or not country endowments are similar enough for diversified production. We explicitly relax the model's assumption of identical technology so

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[1] The same reasoning has been used to address the strong savings–investment correlation among OECD countries, the so-called Feldstein and Horioka (1980) puzzle. With countries inside the same cone, the observed absence of large net capital flows can be reconciled with persistent differences in saving rates across OECD countries. High-saving countries accumulate capital faster than low-saving countries. In the multi-sector HO world, the high-saving countries will therefore produce and export more capital-intensive products without inducing increasingly different returns to capital that should trigger ever-larger net capital flows among the OECD. To the best of our knowledge, this explanation first appeared in Kotlikoff (1984).

[2] In a recent paper based on our work, Cunat (2000) reconfirms our results.

[3] See Leamer and Levinsohn (1995).

that factor price equalization is not required. Following Trefler (1993), we introduce factor-augmenting technological differences across countries, which allow countries to have different factor returns and different sector-level capital–labor ratios even when they belong to the same cone of diversification.

The paper is structured as follows. Section 2 introduces Deardorff's lens condition that forms the theoretical basis for the analysis. We focus on the empirical implementation in Section 3 and describe the data that we use in Section 4. In Section 5, we summarize our main results. The potential effects of factor intensity reversals, aggregation, transportation costs, etc. on our results are described in Section 6. The robustness of our findings is checked in Section 7, where we study measurement errors and sectoral aggregation statistically, and also draw the lenses with different data sets. The last section concludes.

2. Deardorff's lens condition

In the $2 \times 2 \times 2$ Heckscher–Ohlin model, both countries produce both goods if their endowment ratios are similar enough. Similarly, in a multi-country and multi-sector world, countries may or may not be able to produce the same set of goods depending on how similar their factor endowments are. In this section we describe a criterion, called the lens condition, that Deardorff (1994) develops to distinguish a world of diversified production in which all countries can produce the same goods from one in which they cannot. The lens condition is the higher dimensional counterpart of the condition for factor price equalization from the $2 \times 2 \times 2$ model that the country endowment point must lie in the cone of diversification.[4]

The lens condition is perhaps most easily understood with an example. Consider Fig. 1 for a world with three countries and five sectors. Each diagram shows two lenses; the one in dashed lines is the country lens and the other one in solid lines the goods lens. To draw the country lens, countries' endowment vectors for capital and labor, $v_{\mathrm{c}} = (L_{\mathrm{c}}, K_{\mathrm{c}})$, are ranked according to capital–labor ratio. Next, these vectors are concatenated, first in increasing and then in decreasing order of their capital–labor ratios, both times starting from the origin. The goods lens is constructed in a similar fashion. This time we concatenate the sectoral factor use vectors, $z_i = (K_i, L_i)$, where K_{i} and L_{i} are, respectively, the total amount of capital and labor used in sector i in all the countries for which the lenses are drawn. In

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[4] Deardorff's analysis builds on Dixit and Norman's (1980) Integrated World Economy (IWE) and shows that his condition is necessary for factor price equalization and diversified production for the whole world. While Deardorff's formulation also allows for multiple factors, Demiroglu and Yun (1999) show that the condition is not sufficient when there are more than two factors. The sufficiency for two factors is established by Qi (1998) and Xiang (2001). Yun (2002) presents those earlier results together with new ones in a new framework.

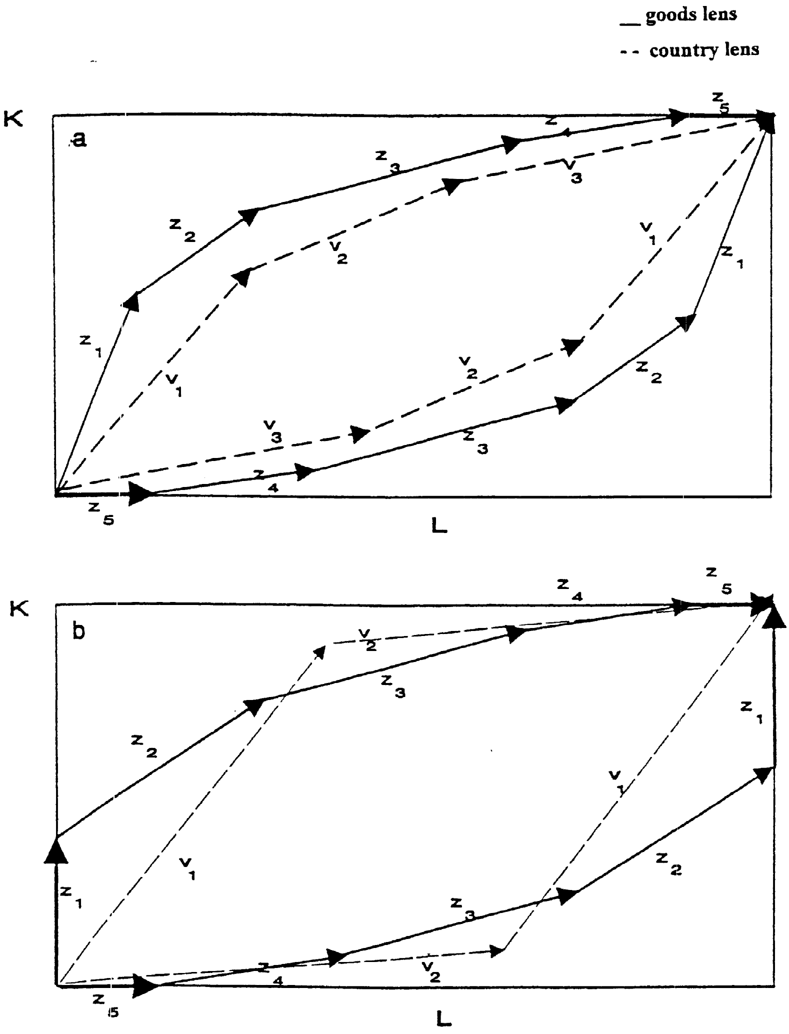

Fig. 1. Example for lens condition: (a) satisfied, (b) violated.

Fig. 1a, Deardorff's lens condition is satisfied: the country lens lies inside the goods lens. In this case, the endowments are similar enough and all countries can produce the same set of goods. Fig. 1b, however, shows a violation. The endowments are not similar enough here and it is impossible that the same set of goods is produced in all countries.

When establishing the sufficiency of the lens condition, Deardorff makes the fairly restrictive assumptions of the Heckscher–Ohlin model for the entire world. We relax these assumptions in several ways. First, we show that Deardorff's lens condition can be used to study any group of countries.[5] One can also restrict the analysis of the lens condition to tradables, which is more appropriate than using all the sectors in the economy for reasons that are discussed in Helpman and Krugman (1985) and Courant and Deardorff (1990). Consequently, only the factors employed in the tradable sectors are used to construct the lenses. In addition, we relax the identical technology assumption and allow for factor-augmenting technological differences between countries. This allows for the possibility that countries lie in the same cone of diversification while they have different factor prices.

One may wonder whether it would be sufficient to check the lens condition by simply comparing the range of factor endowment ratios to the range of factor use ratios. Fig. 1b shows how the lens condition can be violated even when countries' capital–labor ratios lie within the range of the sectoral capital–labor ratios. In other words, the capital–labor ratios of endowments and factor use are sufficient statistics only in the $2 \times 2 \times 2$ model, but not in the multidimensional case. The size of sectors and the size of the endowments are also important in higher dimensions.

3. The empirical implementation

We investigate whether or not the endowment lens lies inside the goods lens. We draw the lenses under various assumptions. Since technology does not appear to be the same throughout world, we introduce factor-augmenting technological differences à la Trefler (1993). We express all factors in US productivity equivalents; we multiply a country's labor by π_{lc} and its capital by π_{kc}, where π_{lc} and π_{kc} measure the labor and capital productivity of country c with respect to the US ($\pi_{\mathrm{lus}}=1$, $\pi_{\mathrm{kus}}=1$). It could be argued that productivity differences are a function of human capital. We therefore also check the lens condition after adjusting the labor endowment for differences in human capital relative to the US. We will denote the relative differences in human capital by π_{hc} ($\pi_{\mathrm{hus}}=1$).

To obtain the country endowments K_{c} and L_{c} for the country lens, we sum for each country c the (productivity-adjusted) factors of its traded goods sectors, as in (1). For the goods lens, we calculate the total amount of (productivity adjusted) capital and labor that is used in sector i by summing the capital and labor used in sector i over all countries, as illustrated in (2). We then draw both lenses as described in the previous section.[6] In the case where we draw both lenses with labor inputs that are adjusted for relative differences in human capital, we multiply

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[5] We provide the proofs of this and some other results in an earlier version of this paper (see Debaere, 1998). The results are available from the authors upon request.

[6] We also draw the lenses without corrections for relative productivity, i.e. assuming $\pi_{\mathrm{lc}}=1$ and $\pi_{\mathrm{kc}}=1$ for each country, so that one can better judge the impact of productivity adjustments.

labor by π_{hc} and assume that π_{kc}, the relative productivity of capital versus the US, equals 1:

$$\begin{aligned} v_{\mathrm{c}} &= (K_{\mathrm{c}}, L_{\mathrm{c}}) \\ L_{\mathrm{c}} &= \sum_{i} \pi_{\mathrm{lc}} L_{\mathrm{ic}} \\ K_{\mathrm{c}} &= \sum_{i} \pi_{\mathrm{kc}} K_{\mathrm{ic}} \end{aligned} \tag{1}$$

$$\begin{aligned} z_{\mathrm{i}} &= (K_{\mathrm{i}}, L_{\mathrm{i}}) \\ L_{\mathrm{i}} &= \sum_{c} \pi_{\mathrm{lc}} L_{\mathrm{ic}} \\ K_{\mathrm{i}} &= \sum_{c} \pi_{\mathrm{kc}} K_{\mathrm{ic}} \end{aligned} \tag{2}$$

4. The data

To construct internationally comparable data for developed and developing countries is a major challenge. In this section we describe the sources of the endowment and factor use data with which we obtain our basic results, and discuss the strategy that we follow to improve the international comparability of the data. The focus is on the production factors capital and labor. We also describe the human capital measures (from Hall and Jones, 1999) and factor price data that we use to proxy for factor-augmenting technological differences between countries. For a detailed discussion of the additional data sets with which we investigate the robustness of our findings, we refer the reader to Appendix A. The sources of these additional data are the Michigan Model (Deardorff and Stern, 1990), the OECD (1997) STAN database, and the skilled and unskilled labor data from the OECD (1996).

4.1. The factor use and factor endowment data

4.1.1. UNIDO and Penn World data

Our analysis requires data for capital and labor inputs in different sectors that are comparable across countries. The sector-level data that form the basis of our analysis are taken from the United Nations Industrial Development Organization (UNIDO). These data are available for 28 manufacturing sectors, which is consistent with our aim to restrict the analysis to tradables. Consequently, for the 28 countries for which we find all necessary data, the country endowments used in those 28 sectors will be the quantities that we use to construct the country lens.[7]

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[7] For the Michigan data and the skilled and the unskilled labor data from the OECD, we are able to include agriculture and mining into the tradable sector. For the list of countries, see Table 1.

Since the sectoral labor data from UNIDO are more easily compared across countries than UNIDO's sectoral investment numbers, we match the UNIDO data with internationally standardized Penn World Table in the following way: (1) Using aggregate capital–labor ratios of the Penn World Tables, we first predict each country's capital–labor ratio for total manufacturing. (2) We then construct a country's labor endowment with UNIDO data, i.e.: we sum all workers in manufacturing. (3) We subsequently multiply this predicted capital–labor ratios for manufacturing with the manufacturing labor endowments and find a country's capital endowment in manufacturing. (With the Yearbook of Labour Statistics data, we correct all labor inputs for international differences in average work hours versus the US.) (4) Finally, to determine the sectoral distribution of the capital stocks within a country, we combine for each country the obtained capital endowment with the sectoral investment flows from UNIDO. This procedure ensures that the total quantity of capital of a country is consistent with other countries as in the Penn World Tables, while the distribution of capital within a country across sectors is determined by the sectoral data from UNIDO. We now describe the data construction process in more detail. We first consider the case without international productivity and human capital differences

Fig. 2 plots the capital–labor ratios k_c and the corresponding per capita GDP's y_c for forty countries. Both series are from the Penn World Tables for the year 1990. The series are in 1985 international prices, in logs, and are adjusted for

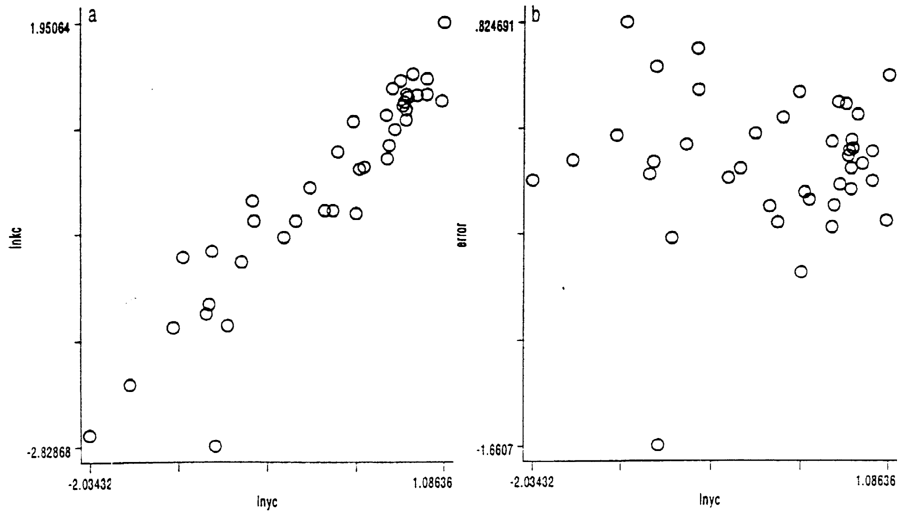

Fig. 2. (a) Capital per hours vs. real GDP per hours, in logs. (b) Error vs. regressor $\ln(y_c)$.

differences in hours worked.[8] There is a strong correlation between k_c and y_c. We exploit that correlation for predictive purposes in the following regression, which can be related to a Cobb Douglas production function. For now, we assume that technology is the same everywhere—we introduce factor-augmenting differences later:

$$\begin{array}{ll} \ln k_c = 0.04 + 1.30 \ln y_c + \epsilon_c & \\ (\text{s.e } 0.07) \quad (\text{s.e. } 0.08) & n{:}40 \quad R^2 = 87.4 \end{array} \tag{3}$$

To predict the capital–labor ratio in total manufacturing for our 28 countries we use their per worker industry GDP from the World Development Indicators (1998) in regression (3). (We adjust this proxy for per worker output in manufacturing for differences in average work hours.)[9] Table 1 lists the predicted capital–labor ratios for manufacturing. We denote these ratios by k_{Mc}. We report the predicted values in levels instead of logs and correct for the bias arising from the logarithmic transformation in the usual way.[10] We next describe how we use the predicted capital–labor ratios for manufacturing to make the UNIDO data internationally comparable.

Since the UNIDO labor data are more easily comparable internationally than the investment figures, we take the labor data as the starting point. We multiply the labor endowment L_c (the sum of all workers in manufacturing in a country, adjusted for differences in hours) by the predicted capital–labor ratio for manufacturing k_{Mc}. In this way we obtain a country's total capital stock as in the next equation:

$$K_c = k_{Mc} \times L_c \tag{4}$$

Thus far, we have the endowment data that are needed to draw the country lens. In order to draw the goods lens we still have to construct sectoral factor use data. For the sector-level labor inputs, we take the labor inputs as found in UNIDO and sum them per sector across countries. To obtain sector-level capital stocks, we combine the within-country distribution of sectoral investment flows from UNIDO with the internationally comparable capital endowments obtained in Eq. (4). We calculate

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[8] These 40 countries constitute the largest set of countries for which we have data available. The countries are: India, Kenya, Israel, Ireland, the US, the UK, Korea, West Germany, Austria, Australia, New Zealand, Norway, Switzerland, Denmark, Belgium, the Netherlands, Paraguay, Argentina, Colombia, Finland, Canada, Sweden, Japan, France, Chile, Peru, Luxembourg, Thailand, Greece, Spain, Portugal, Iceland, Mexico, Sri Lanka, Turkey, Philippines, Guatemala, Jamaica, Hong Kong and Poland.

[9] Due to missing observations, we use Colombia data to proxy for Ecuador.

[10] If b is a normally distributed unbiased estimator of β, then an unbiased estimator for $\exp(\beta)$ is $\exp(b - v\text{ar}(b)/2)$.

Table 1
Capital–labor ratios in manufacturing versus the US with productivity and human capital adjustments

Countries	y_c	k_{Mc}	π_{lc} rel. labor prod.	π_{kc} rel. capital prod.	prod. adj k_{Mc}	π_{hc} rel. human capital	human cap. adj. k_{Mc}
Austria	73	72	116	168	106	67	95
Canada	94	100	114	106	113	91	119
Colombia	28	12	27	57	27	54	21
Cyprus	49	28	47	119	71	71	55
Denmark	68	82	103	161	128	91	100
Ecuador	25	9	25	48	20	61	24
Finland	74	75	79	174	147	86	93
Germany.W.	80	70	96	115	85	80	90
Hong Kong	62	35	64	141	71	74	49
Hungary	29	19	41	64	34	93	22
India	9	2	15	49	7	45	6
Indonesia	13	4	33	42	7		
Ireland	65	41	82	126	66	77	57
Italy	84	69	91	139	107	65	129
Japan	62	42	102	151	63	80	57
Korea, Rep.	44	18	58	92	33	58	32
Malta	24	8	47	63	13	69	19
Netherlands	85	82	104	151	123	80	103
Norway	80	89	87	172	162	91	108
Philippines	13	4	33	61	8	66	8
Poland	20	13	30	54	27	80	21
Portugal	45	30	35	155	97	50	47
Singapore	66	35	50	135	82	55	86
Turkey	24	12	47	63	19	47	21
Egypt	19	6	16	189	43	58	19
UK	73	60	116	143	81	81	79
US	100	84	100	100	100	100	100
Venezuela	47	28	43	55	43	59	65

y_c: per worker real GDP relative to the US, 1985 International prices—Penn World Tables, k_{Mc}: capital per workers in manufacturing, adjusted for differences in hours worked relative to the US, 1985 international prices—own prediction; π_{lc}: rel. productivity of country *c*'s labor versus US, proxied by the relative wage vs. the US, PPP adjusted—ILO Labor Statistics and Penn World Tables; π_{kc} rel. productivity of country *c*'s capital versus the US proxied by the relative price of investment goods vs. the US, PPP-adjusted—Penn World Tables; π_{hc}: the human capital in country *c* versus the US, proxied by relative return to education—Hall and Jones (1999).

for each country the sector-level capital stocks with 15 years of local currency investment data from UNIDO (1976 to 1990). We use the perpetual inventory model, a depreciation rate of 13.3 percent and the 1985 investment deflator from the IMF World Economic Outlook. We then calculate, for each sector *i* and country *c*, the share of *i* in the total manufacturing capital stock of *c*, denoted by s_{ick}. We then multiply these shares with the total manufacturing capital endowment

K_c from expression (4). In this way we obtain internationally comparable sectoral capital stocks (K_{ic}) for all countries:

$$K_{ic} = s_{ick} \times K_c \tag{5}$$

The total capital stock in a sector K_i that we need for the goods lens amounts to the sum of the capital used in a sector in the 28 countries. Note that we have so far not corrected the data for international productivity differences, since we want a benchmark case with which we can compare our results after productivity adjustments.

It is well known that the sectoral capital–labor ratios vary across countries in the data, even though theory says they should be the same for all countries that are in the same cone. Fig. 3 plots for all 28 sectors and all 28 countries, a country's share in the total capital stock of a sector, K_{ic}/K_i, against its share in the total labor that is employed in that sector, L_{ic}/L_i. We see a cloud of capital–labor ratios, even though all points should, in theory, lie on the 45 degree line if countries are in the same cone. For illustrative purposes, we regress K_{ic}/K_i on L_{ic}/L_i.[11] The estimated coefficient is 1.06 and not significantly different from 1 at the 95 percent level. The R^2 is 58 percent. There are various reasons why capital to labor ratios vary

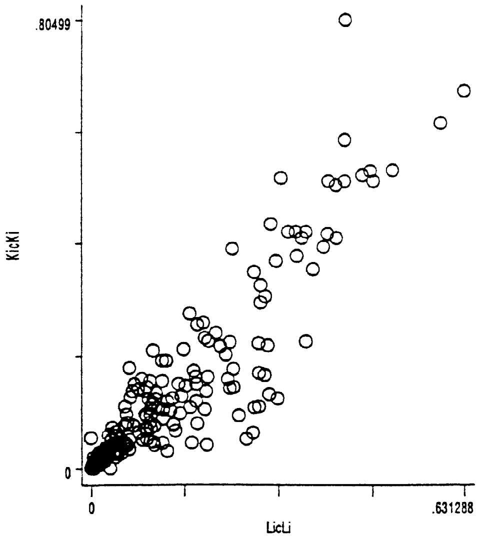

Fig. 3. Country share in sectoral capital vs. sectoral labor.

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[11] Because measurement error is especially a concern for capital, we put K_{ic}/K_c on the left-hand side.

Table 2
Capital–labor ratios across sectors under different assumptions, normalized by US capital–labor ratio or the highest sectoral capital–labor ratio

No. and sector	For world as a whole						For the rich OECD					
	No adjustments		Prod. adj.		Human cap. adj		No adjustments		Prod. adj.		Human cap. adj.	
	vs US	vs highest	vs US	vs highest	vs US	vs highest	vs US	vs highest	vs US	vs highest	vs US	vs highest
311 Food products	0.98	0.10	1.86	0.11	1.42	0.10	1.68	0.12	2.18	0.16	2.03	0.15
313 Beverages	2.94	0.29	5.17	0.31	4.02	0.29	4.62	0.33	5.98	0.43	5.53	0.40
314 Tobacco	0.46	0.05	1.79	0.11	0.95	0.07	4.14	0.30	5.09	0.37	5.09	0.37
321 Textiles	0.53	0.05	1.16	0.07	0.85	0.06	1.12	0.08	1.45	0.11	1.39	0.10
322 Wearing apparel,except footwear	0.20	0.02	0.35	0.02	0.28	0.02	0.29	0.02	0.38	0.03	0.35	0.03
323 Leather products	0.38	0.04	0.73	0.04	0.58	0.04	0.66	0.05	0.86	0.06	0.84	0.06
324 Footwear, except rubber or plastic	0.30	0.03	0.62	0.04	0.46	0.03	0.54	0.04	0.72	0.05	0.70	0.05
331 Wood products, except furniture	0.73	0.07	1.31	0.08	1.04	0.07	1.13	0.08	1.53	0.11	1.34	0.10
332 Furniture,except metal	0.55	0.05	0.82	0.05	0.70	0.05	0.67	0.05	0.87	0.06	0.80	0.06
341 Paper and products	3.56	0.35	5.62	0.33	4.68	0.33	4.57	0.33	6.04	0.44	5.47	0.40
342 Printing and publishing	1.18	0.12	1.66	0.10	1.47	0.10	1.33	0.10	1.70	0.12	1.57	0.11
351 Industrial chemicals	4.36	0.43	7.95	0.47	6.25	0.45	6.88	0.50	9.14	0.66	8.50	0.61
352 Other chemicals	1.59	0.16	2.69	0.16	2.22	0.16	2.33	0.17	2.98	0.22	2.79	0.20
353 Petroleum refineries	10.15	1.00	16.83	1.00	14.04	1.00	13.85	1.00	18.28	1.32	17.13	1.24
354 Misc. petroleum and coal products	1.96	0.19	3.74	0.22	2.96	0.21	3.51	0.25	4.44	0.32	4.07	0.29
355 Rubber products	0.90	0.09	1.66	0.10	1.35	0.10	1.66	0.12	2.17	0.16	2.03	0.15
356 Plastic products	1.35	0.13	1.99	0.12	1.75	0.12	1.56	0.11	1.99	0.14	1.87	0.14
361 Pottery, china, earthenware	2.11	0.21	3.66	0.22	3.45	0.25	2.82	0.20	4.01	0.29	4.16	0.30
362 Glass and products	1.74	0.17	2.97	0.18	2.35	0.17	2.68	0.19	3.41	0.25	3.12	0.23
369 Other non-metallic mineral products	1.27	0.13	2.43	0.14	1.86	0.13	2.12	0.15	2.76	0.20	2.50	0.18
371 Iron and steel	2.19	0.22	4.00	0.24	3.16	0.23	3.30	0.24	4.39	0.32	4.06	0.29
372 Non-ferrous metals	2.25	0.22	3.97	0.24	3.13	0.22	3.20	0.23	4.31	0.31	3.83	0.28
381 Fabricated metals	0.84	0.08	1.33	0.08	1.12	0.08	1.07	0.08	1.41	0.10	1.30	0.09
382 Machinery, except electrical	1.26	0.12	1.84	0.11	1.63	0.12	1.54	0.11	1.95	0.14	1.87	0.14
383 Machinery, electric	1.29	0.13	1.91	0.11	1.70	0.12	1.55	0.11	2.01	0.14	1.91	0.14
384 Transport equipment	1.63	0.16	2.68	0.16	2.21	0.16	2.22	0.16	2.92	0.21	2.69	0.19
385 Professional and scientific equipment	1.28	0.13	1.72	0.10	1.56	0.11	1.47	0.11	1.81	0.13	1.71	0.12
390 Other manufactured products	0.58	0.06	0.90	0.05	0.76	0.05	0.78	0.06	1.00	0.07	0.93	0.07

Sources: UNIDO, Penn World Table, Hall and Jones (1999), ILO Yearbook. See Table 1 for description of adjustments.

across countries. One explanation is, of course, that countries may lie in different cones. But different capital–labor ratios can also be due to differences in technology, measurement error and sectoral aggregation. We will discuss these concerns in more detail below. Table 2 reports the sectoral ratios K_i/L_i for the two groups of countries for which we draw the lenses, i.e. the mixed group of developed and developing countries and the group of rich OECD countries. We normalize the capital–labor ratios by the total capital–labor ratio of the US, which makes the numbers comparable with Table 1.

Because of technological differences between countries, we also investigate the lenses with productivity-adjusted factors. We follow Trefler (1993) and proxy for labor- and capital-augmenting productivity difference (π_{lc} and π_{kc}) between a country and the US with the (PPP-corrected) relative wage and the (PPP-adjusted) difference in the price index of investment goods. In the next section we discuss the proxies at length and comment on the rationale for using them. We base the prediction of manufacturing's capital to labor ratio for our 28 countries on regression (6) that now explicitly includes factor-augmenting productivity differences:

$$\begin{array}{llllll} \ln k_c = & 2.1 + & 1.26 \ln y_c + & 0.31 \ln \pi_{kc} - & 0.41 \ln \pi_{lc} + \epsilon_c & \\ \text{(s.e.)} & (1.4) & (0.15) & (0.20) & (0.29) & R^2 = 88.5 \end{array} \qquad (6)$$

As before, we plug the per capita industry GDP's y_c in the regression to predict k_{Mc}. Note that the coefficients on k_c and l_c are significant only at the 85 percent level. Given the small sample and the theoretical justification for both variables, however, we keep them in the regression. With the predicted k_{Mc}, we construct capital use and endowment data in the same way as before. We then translate the capital and labor numbers into productivity equivalents by premultiplying them with the capital productivity differences k_c and the labor productivity measures l_c as suggested by Eqs. (1) and (2). Table 1 contains the relative factor returns and the productivity-adjusted capital–labor ratios versus the US. Note that the introduction of factor-augmenting differences reduces the variation in capital–labor ratios. To summarize the effect of productivity corrections, we run the regression of the productivity adjusted K_{ic}/K_i on the productivity adjusted L_{ic}/L_i. The coefficient is 1.04 and not statistically different from 1. Compared to the regression without productivity corrections, the R^2 increases from 58 to 80.5 percent.

Finally, to take into account differences in human capital, we include international differences in human capital π_{hc} in regression (7). As before, we base our prediction of the capital–labor ratio in manufacturing on regression (7), We discuss our proxy for π_{hc}, the relative return to education in a country versus the US, in Section 4.2:

$$\begin{array}{lllll} \ln k_c = & 0.34 + & 1.12 \ln y_c + & 0.81 \ln \pi_{hc} + \epsilon_c & \\ \text{(s.e.)} & (0.18) & (0.12) & (0.44) & R^2 = 88.4 \end{array} \qquad (7)$$

With the predicted capital–labor ratio for manufacturing in a country, we calculate capital as before and multiply the labor numbers with π_{hc} to adjust them for human capital differences. The obtained capital–labor ratios that are adjusted for international differences in human capital are reported in Tables 1 and 2.

4.1.2. The Hall and Jones data on human capital

The human capital measures that we use are taken from Hall and Jones (1999). Hall and Jones use the cross-country survey evidence on the returns to schooling from Psacharopoulos (1994) to construct human capital stocks. In their analysis, human capital augmented labor is given by $H_{\mathrm{i}} = e^{\varphi(E_{\mathrm{i}})}L_{\mathrm{i}}$, where $\varphi(E_{\mathrm{i}})$ reflects the efficiency of a unit of labor with E years of schooling relative to one with no schooling, $\varphi(0)=0$. The derivative $\varphi'(E_{\mathrm{i}})$ yields the return to schooling that can be estimated in a Mincerian wage regression. Based on Psacharopoulos' survey, Hall and Jones assume that (E_{i}) is piecewise linear with a return to education of 13.4 percent in the first four years of education, 10.1 for the next four years, and 6.8 for the years beyond the 8th year. Hall and Jones (1999) provide, for 1988, human capital–labor ratios for all our countries with which we can upgrade the labor force. The ratio is reported in Table 1 for the UNIDO countries and Table A.1 for the Michigan Model countries. We then multiply the sectoral labor use data for each country with its respective human-capital/labor ratio.

4.2. Factor prices

An alternative way to correct for productivity differences between a country and the US is to rely on relative factor prices. As in Trefler (1993), we draw the wages from the Yearbook of Labour Statistics for 1990 and make them internationally comparable with the consumption PPP from the Penn World Tables. Most data are hourly wages. In case the hourly wages are not available (e.g. when monthly wages are given instead) we divide the wage numbers by the hours worked from the same Yearbook of Labour Statistics. For missing data we use the data for countries that are similar in terms of per capita GDP and region.[12] As can be seen in Table 1, the most significant differences are obtained between developed and developing countries, as one would expect. To find a convincing proxy for differences in returns to capital is more difficult and more open to criticism. We follow Trefler (1993) in choosing the 1990 PPP-adjusted investment price index from the Penn World Tables. The values are reported in Table 1. The price tends to be lower in developing countries relative to developed ones. Note that there are also significant differences in the investment price index among developed countries.

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[12] We approximate the Italian wage with the French wage, the Ecuadorian with the Colombian, the wage in Malta with the Turkish wage and for Indonesia we use the wage in the Philippines.

From a theoretical point of view, differences in factor returns are the appropriate technology correction when there is factor price equalization. If countries are not lying in the same cone, however, the relative factor returns are likely to overstate technological differences; for example, labor-abundant countries would have lower

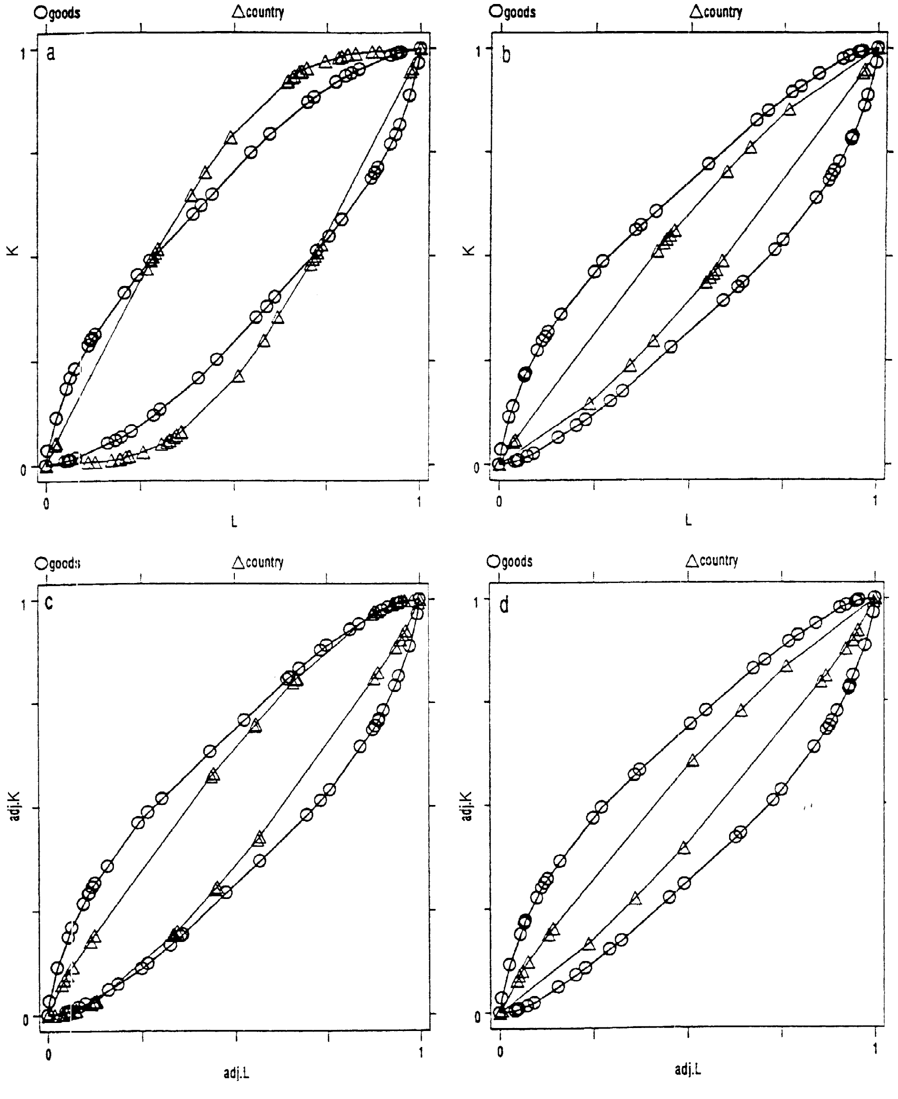

Fig. 4. Lens in the data (a) World without adjustments. (b) OECD without adjustments. (c) World with productivity adjustments p_c and q_c. (d) OECD with productivity adjustments q_c and p_c. (e) World with human capital adjustments. (f) OECD with human capital adjustments.

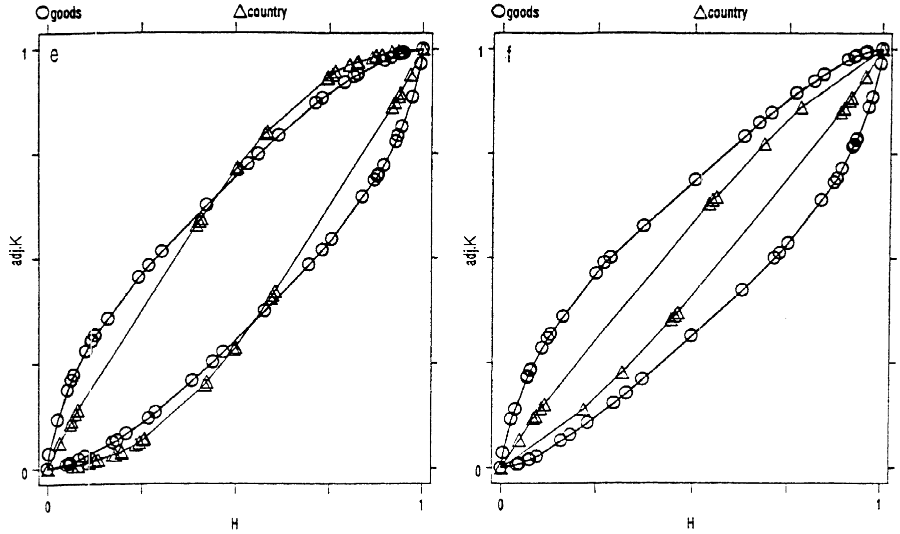

Fig. 4. (*continued*)

wages and higher returns to capital even if there were no differences in technology. Trefler's productivity corrections have drastic implications for the endowments, especially among developing countries. In most cases their endowments shrink dramatically. Moreover, due to the relatively low labor productivity of developing countries, differences in capital–labor ratios between developed and developing countries are significantly reduced. (Note that the latter makes a violation of the lens condition less likely.) Because of this bias, we prefer our results with human capital corrections. We interpret the suggested productivity correction with factor prices as a robustness check of our results.

5. The empirical results

The main point of our analysis comes to the fore most clearly when the left and right panels of Fig. 4 are compared. The lenses to the left are the ones for a mixed group that includes both developed and developing countries. The diagrams to the right only consider rich OECD countries. The different rows of diagrams in Fig. 4 correspond to different data sets and productivity adjustments. Clearly, a violation of the condition is obtained for the mixed group in all the cases, whereas no violation is found for the group of rich OECD countries.

The panels a–d in Fig. 4 present the lenses drawn with UNIDO and Penn World data. In panels a and b the lenses are drawn without any adjustments for international productivity differences. Both panels provide a benchmark to assess the impact of various corrections, which we present in Fig. 4c–f. Labor is on the horizontal and capital on the vertical axis. We normalize the total group endowments to one, so that each side of the endowment box has unit length. If all countries had the same factor endowment ratios, the country lens would be the diagonal of the box. The proximity of the country lens to the diagonal gives an indication of the relative similarity of the capital–labor ratios of countries in a group. For the mixed group that includes both developed and developing countries, we obtain violations of the lens condition (Fig. 4a, c and e). For the group of rich OECD countries, the condition is satisfied – the country lens always lies inside the goods lens (Fig. 4b, d and f)

We also adjust the data for productivity differences. As discussed in detail above, we follow Trefler (1993) and use the relative price of investment as a proxy for the productivity differences for capital and the PPP-adjusted relative wages for labor productivity. The productivity corrections drastically reduce the share of the non-OECD countries in world capital and labor. The developing countries are bunched together near the corners, where they violate the lens condition. (This violation will be seen more easily with the numerical measures provided below. We also note that it is not the case that one country is responsible for the violation.) As mentioned before, we consider the violation in Fig. 4c after the rather drastic productivity corrections an indication of the robustness of the result. Fig. 4e and f show what happens in case one introduces differences in human capital. Because of data constraints, we adjust a country's labor with the same human capital correction hc in all sectors. Still, the outcome remains the same: a non-violation for the rich OECD countries and a violation for the world as a whole.

In some cases (e.g. in Fig. 4c) it is difficult to check the lens condition by visual inspection. We introduce a measure that indicates how well the country lens lies inside the goods lens and report its value in Table 3 under 'Measure'. A positive value indicates that the lens condition is satisfied and a negative value indicates a violation. The highest value for the measure is one, which is reached when the country lens is the diagonal, i.e. when all countries have the same factor endowment ratio. A very small positive number indicates that the lens condition is barely satisfied. The measure is derived as follows. Consider the diagonal of the endowment box between the points (0,0) and (1,1). For any point x on that diagonal, we draw a line perpendicular to the diagonal through the point x. Call $c(x)$ the point at which the perpendicular intersects the country lens and $g(x)$ where it intersects the goods lens. Let $d(y,z)$ represent the distance between any two points y and z. The measure is then defined as:

$$\min_{x}\left\{1-\frac{d(x,c(x))}{d(x,g(x))}\right\}$$

As can be seen in Table 3, the measure always takes on negative values (indicating

Table 3
Introducing measurement error

Country group	Adjustment	Dataset	Prob (Violation) (%)	Sigma	Measure	Measure with disaggregation
1 World	None	Mich	100.00	1.19	−0.82	−0.79
2 World	Hum. capital	UNIDO	98.55	1.08	−0.40	−0.36
3 World	Hum. capital	Mich	100.00	1.04	−0.94	−0.89
4 World	Prod. adj.	UNIDO	96.10	1.13	−0.16	−0.14
5 World	Prod. adj.	Mich	98.60	0.70	−0.50	−0.29
6 OECD	None	STAN	0.45	0.59	0.44	0.49
7 OECD	None	Mich	0.00	0.40	0.51	0.57
8 OECD	Hum. capital	UNIDO	1.10	0.48	0.37	0.44
9 OECD	Hum. capital	STAN	6.80	0.65	0.23	0.29
10 OECD	Hum. capital	Mich	0.05	0.46	0.49	0.53
11 OECD	Prod. adj.	UNIDO	0.20	0.51	0.53	0.55
12 OECD	Prod. adj.	STAN	16.25	0.68	0.13	0.20
13 OECD	Prod. adj.	Mich	0.00	0.45	0.50	0.54

Notes: The number of repetitions for each simulation is 2000. See Table 1 for the sources of the productivity adjustments.

Sigma: Average std. dev. of the log K/L ratios for sectors across countries as obtained from the data.

Measure: Positive if no violation of lens condition, negative if violation.

Measure with disaggregation: The new value of the measure when the lenses are adjusted for within-sector K/L variation.

Prod. adj.: With productivity-adjusted labor and capital, based on factor awards relative to the US.

Human capital: After adjustment for differences in human capital, proxied by differences in return to education.

that the lens condition is violated) for the mixed group, and positive values (no violation) for the OECD. We come back to these numbers in Section 7.3.

Other than helping the visual inspection, the measure we propose is appealing in two additional ways. First, by looking at the ratio of the distances of the country and goods lenses to the diagonal, we correct for the fact that the country and goods lenses come together near the corners of the graph. Second, our measure depends only on the point where the two lenses come closest to one another. It is therefore sufficient that the two lenses touch or cross at a single point in order to make our measure non-positive. The discussion in Section 6.1 will make clear that the latter is a desirable property because the presence of multiple diversification cones can manifest itself through lenses touching each other at a single point, while the lenses may be apart elsewhere.

6. Some theoretical and empirical considerations

To give the reader a better sense of our analysis, we discuss how the shape of the goods lens is affected by specialization of production, sector-level aggregation, transportation costs, factor intensity reversals, and exclusion of countries and factors.

6.1. The case of complete specialization

We first study what happens to the lenses in case countries are completely specialized and produce different sets of goods. Fig. 5 presents the standard Lerner–Pearce diagram with unit-value isoquants (denoted by G_i for good i) for a world with several goods and several countries. There are two cones of diversification. Suppose countries 1, 2 and 3 are capital abundant and suppose their endowments lie in cone 1. The three countries specialize in the four most capital-intensive sectors. Countries 4, 5 and 6 are labor-abundant and lie in cone 2. They specialize in the most labor-intensive goods. The lenses that correspond to this situation are depicted in Fig. 6. The goods lens is shown with solid and the country lens with dashed lines. The vectors v_1, v_2 and v_3 are the endowment vectors of countries 1, 2 and 3 and the vectors $\mathbf{z}_1$, $\mathbf{z}_2$, $\mathbf{z}_3$ and $\mathbf{z}_4$ are the factor use vectors for the four capital-intensive sectors. Note that $v_1 + v_2 + v_3 = \mathbf{z}_1 + \mathbf{z}_2 + \mathbf{z}_3 + \mathbf{z}_4$. This is the case because the countries 1–3 produce the goods 1–4. Therefore, the goods lens touches the country lens and violates the lens condition at the endpoint of v_3. Of course, such a clear-cut situation is never seen in the data.

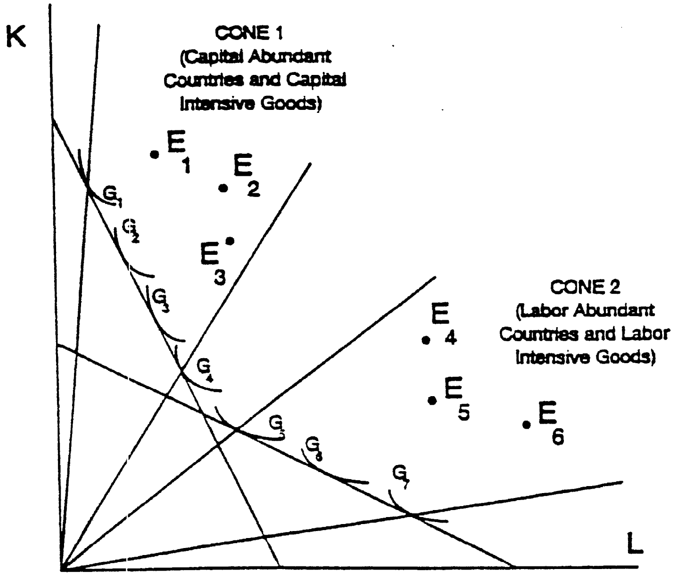

Fig. 5. Groups of countries that specialize.

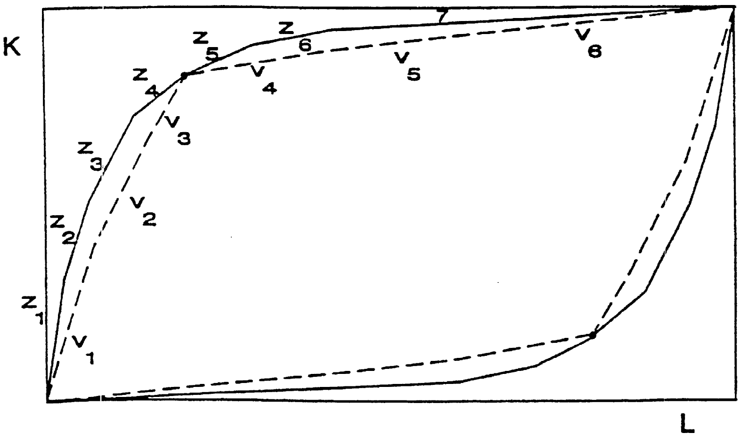

Fig. 6. Country and goods lens that correspond to Fig. 5.

Sectoral data are highly aggregated and all countries appear to produce most of the goods.[13] We discuss the effects of sectoral aggregation below in Section 6.3.

6.2. Looking at a subset of countries

Here we offer a visual illustration of what happens when we exclude some of the countries from the analysis, and why the lens condition is still a valid criterion for a group of countries rather than the whole world. For the formal proof of the argument we refer the reader to an earlier version of this paper.[14] As argued above, in Figs. 5 and 6 one group of countries lies in the capital-intensive and the other in the labor-intensive cone. If we draw the lenses only for the capital abundant group, we obtain the smaller box in the lower left portion of the original endowment box in Fig. 7. The lens condition is satisfied for this smaller box, which is consistent with the fact that the countries in this group lie in the same cone. As soon as we include countries from the other cone that produce different products, however, the two lenses touch each other and thus violate the lens condition.

6.3. The problem of sectoral aggregation

Each of the sectors in the data is likely to contain a variety of subsectors with different factor intensities. For that reason, a sector's capital–labor ratio could

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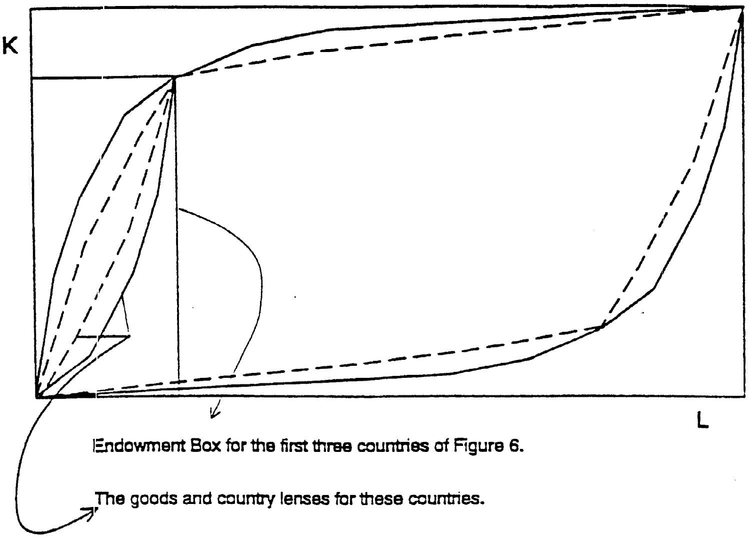
[13] Note that that there is the theoretical possibility that the lenses could touch each other for a group of countries that are in the same cone. For the purposes of this empirical paper, this measure-zero theoretical possibility is irrelevant and will be ignored here and elsewhere in this paper. Incidentally, the violations that we obtain are typically not borderline.

[14] See Debaere (1998).



Endowment Box for the first three countries of Figure 6.

The goods and country lenses for these countries.

Fig. 7. Lenses for a subset of countries.

differ in the data across countries that are in the same cone, even though it should be the same in theory. Sectoral aggregation does not affect the shape of the country lens, but it makes the goods lens thinner. We again provide a graphical illustration of the argument.[15] In Fig. 8, we aggregate the sectors 1–3 into a single sector. The original factor use vectors ($\mathbf{z}_1$, $\mathbf{z}_2$ and $\mathbf{z}_3$) are replaced with a new factor use vector $\mathbf{z}_{1,2,3}$. The new goods lens violates the lens condition, although there was no violation before. Aggregation raises an important issue for the interpretation of the empirical results that were presented in the Section 5. On the one hand, aggregation suggests the possibility that a violation of the lens condition for the mixed group of countries may have been generated spuriously because of sectoral aggregation. On the other hand, it reinforces the finding of a non-violation for the OECD countries, since it is obtained despite sectoral aggregation that makes a violation more likely.

In order to understand the potential impact of sectoral aggregation on the shape of the goods lens, we perform a disaggregation exercise in which we incorporate the firm-level variation in the capital–labor ratios within sectors. We use firm-level data for the US from COMPUSTAT for that purpose, and find that sectoral aggregation is most likely not the reason why the lens condition is violated for the whole world. We now describe our disaggregation procedure in detail.

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[15] See Debaere (1998) for a formal proof.

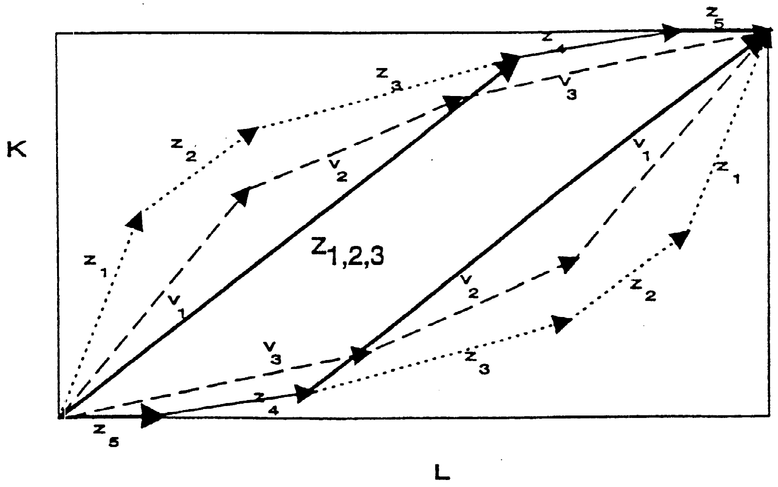

Fig. 8. The effect of aggregation.

We first calculate the average within-industry variation in the firm-level log capital–labor ratios.[16] We then make a generous assumption that exaggerates the effect of aggregation. We assume that all of the within-industry variation is due to aggregation. We then study the impact on the lenses. We break down all the sectoral factor use vectors (for each sector in each country) into 100 equal parts, as if there were 100 firms.[17] We then perturb these 100 identical factor use vectors so that their new capital–labor ratios are distributed randomly, with a mean that equals the industry's original capital–labor ratio and a variance equal to the value that comes from COMPUSTAT. In order to make sure that the generated firm-level vectors add up to the original factor use vector, we then scale the firm-level vectors. We subsequently draw the hypothetical 'disaggregated' goods lens using those pseudo firm-level data. The 'Measure with Disaggregation' in the last column of Table 3 reports the new values of the measure—as before, a positive number indicates a non-violation, whereas a negative number a violation. (Since the goods lenses become thicker when we 'undo' sectoral aggregation, the measures increase.) Of interest are the lenses for the mixed group of countries, referred to as 'World'. The measure remains negative in all those cases. In fact, disaggregation does not appear to make a substantial difference except for case 5, where the measure goes up from -0.50 to -0.29.

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[16] The average standard deviation of $\log(K_{\mathrm{if}}/L_{\mathrm{if}})$ of firm f within its respective 3-digit industry i is 0.47, which is quite substantial.

[17] We experimented with different values for the number of firms in an industry. As long as there are more than 30 firms, the number of firms does not make a noticeable difference in the shape of the disaggregated goods lens.

6.4. Factor intensity reversals

A factor intensity reversal occurs when a good is capital-intensive in one country and labor-intensive in another. Fig. 9 demonstrates such a case. Countries *A* and *B* have the same technology, but good *X* is produced capital intensively in the capital-abundant country *A* and labor intensively in the labor-abundant country *B*. (Good *Y* is produced with Leontief technology and the same capital intensity in both countries.) Although both countries produce both goods, the price change of good *Y* will affect the countries in a different way. An increase in the price of *Y* will induce an increase in the return to capital with respect to the wage in country *A*, and the reverse in country *B*. We, therefore, would prefer to see a violation of the lens condition in the case of a factor intensity reversal. With the graphical example of Fig. 9, we show that the effect of factor intensity reversal on the lenses is similar to that of sectoral aggregation; it makes the goods lens thinner and thus make a violation of the lens condition more likely. Consider the world-wide factor use vector for good *X* that is obtained by summing up the sectoral factor use vectors for good *X* from the two countries. That vector will have an average factor intensity that is nearly the same as that of good *Y*. The goods lens will consequently be a thin one and will trigger a violation of the lens condition.

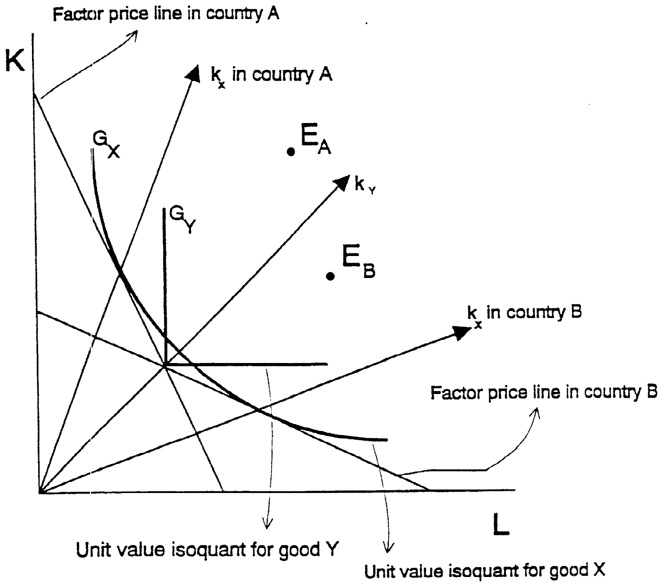

Fig. 9. Factor intensity reversal.

6.5. Factors of production that are left out

In this paper we investigate the similarity of country endowments for capital and labor only. We leave out other production factors such as land and human capital due to data limitations. It is entirely possible, however, that a country *A* is similar to a country *B* in terms of capital and labor endowment, yet unable to replicate *B*'s production because it lacks a third factor. This is a caveat that should be attached whenever we find that the lens condition is satisfied. (Omitted factors cannot alter the conclusion when we find a violation.)

To explore the implications of human capital differences, we checked the lens condition using Hall and Jones' human capital data. In addition, we present in Section 7.4 an exercise with skilled and unskilled labor for a limited number of OECD countries. In either case, accounting for human capital does not reverse our conclusion that developed countries are in the same diversification cone. We do not have the appropriate data to explore the impact of land. It is an open question how land would affect our findings for the developed OECD. Our sense is, however, that for most of the goods that OECD countries produce, country land endowments are not a bottleneck.

6.6. Transportation costs

Deardorff (1994) develops his condition in a world with identical technologies and frictionless trade, i.e. without transportation costs or trade barriers. We are aware of the fact that these requirements do not hold exactly in reality. For instance, recent empirical work by Hummels (1999a,b) underscores the significance of transportation costs. Transportation costs could alter the interpretation of our results. For instance, we find that developing countries do not appear to be in the same cone as developed countries, so that both produce different goods and a drop in the price of developing country exports will not affect the scarce factor in developed countries negatively and help its abundant factor. If transportation costs are sufficiently high, however, they may enable domestic producers to compete with cheap imports and survive in developed countries. In that case, indeed, price drops of developing country exports will have an impact in the developed world. There is no obvious way to address this concern in the present framework.

7. Robustness of the results

We already presented some evidence of the robustness of our empirical findings by studying productivity and human capital adjustments in Section 5 and the impact of disaggregation in Section 6. In this section we draw the lenses with additional data from the Michigan Model (Deardorff and Stern, 1990), the OECD STAN data, and the skilled and unskilled labor data from the OECD. Finally, we investigate the impact of measurement error.

7.1. The lenses in the Michigan model

The Michigan Model (Deardorff and Stern, 1990) provides data for 33 developed and developing countries.[18] As opposed to the UNIDO data that contain sectoral investment flows with which one can construct capital stocks, for the Michigan data sectoral capital stocks are mainly imputed based on the available

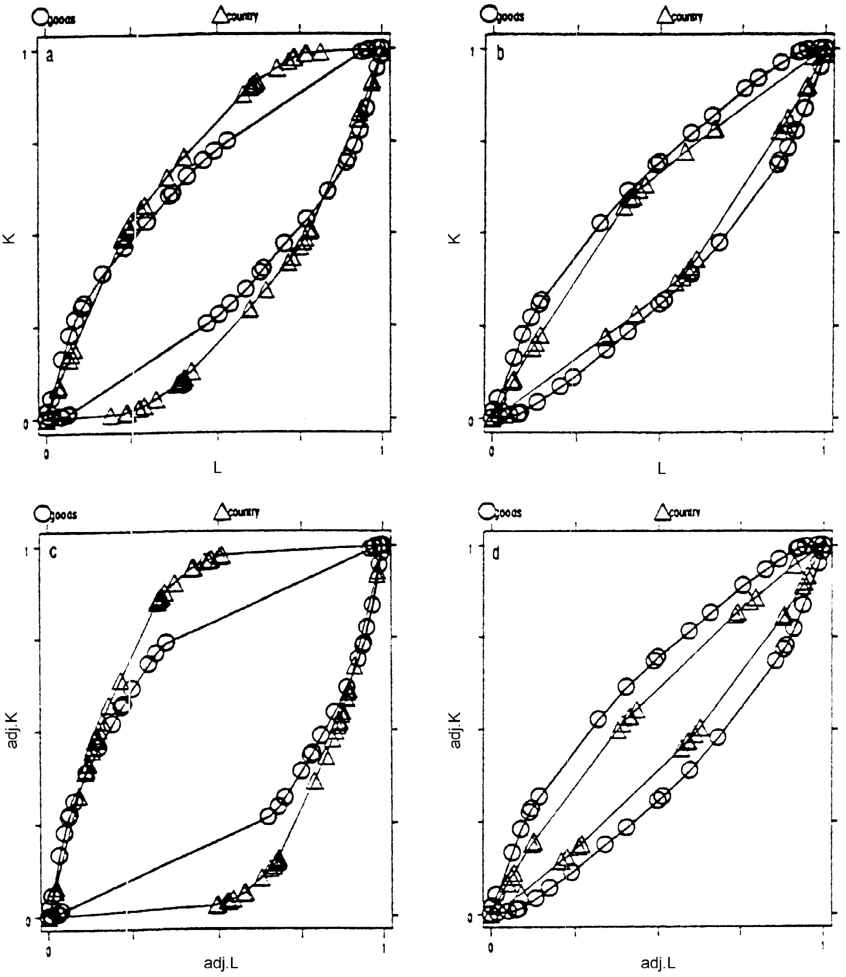

Fig. 10. Lens in the data (a) World without adjustments. (b) OECD without adjustments. (c) World with productivity adjustments p_c and q_c. (d) OECD with productivity adjustments q_c and p_c.

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[18] For a detailed description, we refer to the '1990 Michigan Model Database—Documentation'.

sector level data for the US and Canada. Appendix A describes the imputation procedure at length. For all sectors (traded and non-traded) in a country, sectoral output is multiplied by the capital–output ratio of that sector in the US and Canada. Next, each country's sectoral capital data are added together and rescaled so as to match the estimates of the country's total capital endowment based on World Bank data. The list of countries and traded goods sectors that we use for the analysis are reported in Table A.1. An advantage of the Michigan Model data is that we can include agriculture and mining in the traded goods sector. We also adjust the data with π_{hc} for human capital differences, π_{lc} for labor productivity differences, and π_{kc} for differences in capital productivity. The data are reported in Tables A.1 and A.2. As can be seen from the lenses in Fig. 10, we observe the same pattern as before: a violation for the group of developed and developing countries, and no violation for the rich OECD countries.[19] (Table 3 has the values for the measure for all the four cases in Fig. 10 as well as the two cases without any productivity adjustment.)

7.2. OECD STAN data

The STAN data set provides internationally comparable industry-level employment and investment data for the OECD. Fig. 11 presents the goods and country lenses for the rich OECD countries.[20] In Appendix A, we provide more detail and

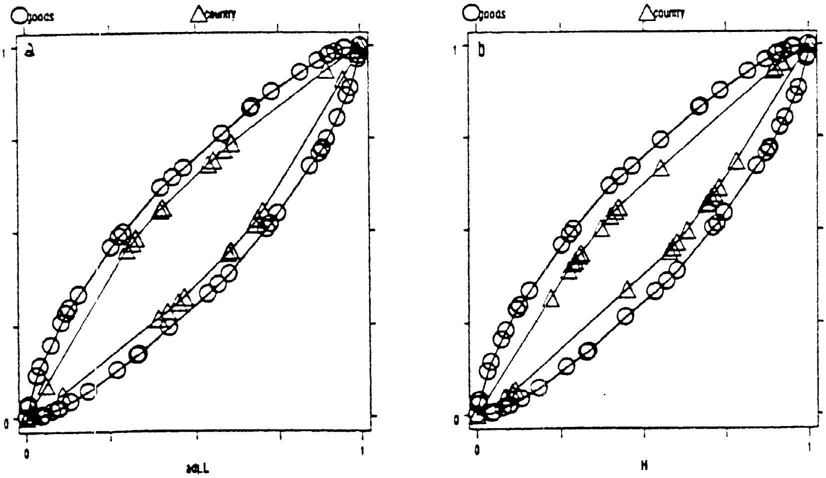

Fig. 11. STAN.

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[19] The rich OECD countries in this case are France, Germany, Belgium, the Netherlands, the UK, the US, Canada, Denmark, Norway, Sweden, Italy, Japan, Austria, Finland, Australia and New Zealand.

[20] We use the same set of developed countries that we were able to select in the Michigan Model.

discuss at length how we construct the sector-level capital stocks. As before, we use factor-augmenting productivity differences (Fig. 11a) and corrections for human capital (Fig. 11b). We find no violation of the lens condition for this set of countries, which confirms our previous results.

7.3. Introducing measurement error

Measurement error in our data is a concern, especially for capital. We run Monte Carlo simulations to study its effect. We use the cross-country variation in sectoral capital–labor ratios as an indicator of measurement uncertainty. In theory, the capital–labor ratio for a sector can be different across countries when there is sectoral aggregation or if there is no factor price equalization. We make the generous assumption that all the cross-country variation in sectoral capital–labor ratios is due to measurement error. This variation is substantial. In Table 3, 'Sigma' denotes the average standard deviation of the log capital–labor ratio in a sector across countries. For example, when sigma is 0.50, the standard deviation for a given quantity (capital or labor in a sector in a country) of a perturbation due to measurement error is 36.5 percent.[21]

We then generate fictitious data with 2000 repetitions for each lens. We perturb the capital and labor data for each sector in each country by randomly drawn errors with mean zero and a variance that corresponds to the standard deviation of the sectoral log capital–labor ratios ('Sigma'). We count the number of times that the simulated data violate the lens condition, and divide that number by 2000 to obtain the probability of a violation. The results for the different data sets are presented in Table 3 under the column 'Prob (Violation)'. For the mixed group of countries (first five rows denoted 'World'), a violation is obtained in over 96 percent of the cases. (For this group, it is desirable to have the probabilities close to 100 percent since it indicates that perturbing the data with measurement errors does not tend to reverse the violation result.) As for the rich OECD countries (where a low Prob(Violation) supports our results), a violation is found in less than 1.1 percent of the cases except for the STAN data, where violation probabilities of

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[21] We compute the standard deviation of the log capital–labor ratio for each sector across countries, and use the average as the standard deviation of the measurement error for all observations. The error may arise from the measurement of capital, labor, or both. Attributing the error to one or the other does not make a notable difference in the final result. For the numbers we report in Table 3, it is assumed that capital and labor are equally responsible for measurement errors. The errors in capital and labor (for any given sector in a country) are assumed to be independent. When the standard deviation equals 0.50, the standard deviation of $\ln(K)$ and $\ln(L)$ is $0.50/\sqrt{2}$. We also correct for the bias that a lognormal disturbance generates by dividing the new figures by $\exp(\mathrm{Var}(\sigma)/2)$, where σ is the standard deviation of the error with which we perturbed the original quantity in logs. Such a perturbation results in a variation of 36.5 percent in capital and labor. In trials where we assume all the variation in the capital–labor ratios across countries is due to measurement error in capital, the one-standard perturbation in capital in each sector in each country becomes 53.3 percent of its base value.

6.8 and 16.3 percent are obtained when factors are adjusted for differences in human capital and differences in factor-augmenting productivity. Those probabilities are larger than the customary 5 percent p-values, but they are nevertheless small, and are obtained in the presence of sectoral aggregation that biases the lenses toward a violation.

As mentioned above, all of the variation in sectoral capital–labor ratios across countries is attributed to measurement error. This probably overstates the size of actual errors because part of that variation is certainly due to aggregation. Each sector contains various subsectors with different capital–labor ratios, and variation in the within-sector composition across countries will result in different capital–labor ratios for a given sector in different countries. On the other hand, our analysis of measurement errors ignores the potential within-country correlation of measurement errors.

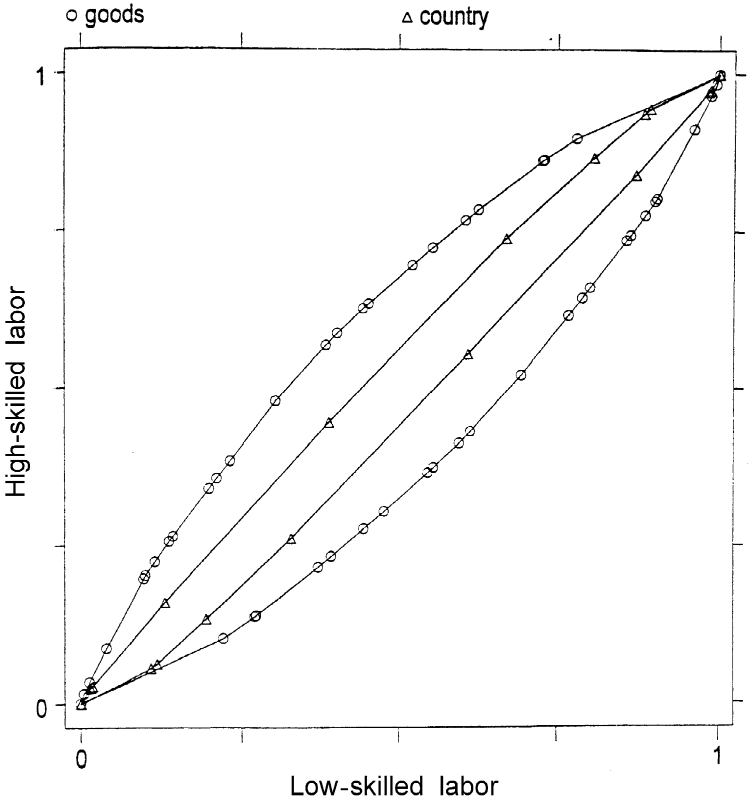

Fig. 12. OECD high-skilled vs. low-skilled labor.

7.4. High-skilled versus low-skilled labor

Finally, we check the lenses with high- and low-skilled labor for a set of countries for which the OECD provides internationally comparable data. The countries are Australia, Finland, France, Germany, Italy, Japan, New Zealand, the UK and the US. Skilled labor is defined in two different ways: either white- vs. blue-collar workers, or high-skill white-collar workers vs. the rest. (We provide the details in Appendix A.) As before, we draw the goods lens for tradables—manufacturing, agriculture and mining. For both definitions of skilled labor, we obtain no violation. The lenses for the narrower definition of skilled labor (high-skilled white-collar) are shown in Fig. 12.

8. Conclusion

We investigate whether country endowments are similar enough to allow the production of the same set of goods in all countries of the world. We rely on the lens condition of Deardorff (1994) that extends the diversification cone to higher dimensions. The evidence suggests that there is more than one cone of diversification for the world as a whole, whereas the rich OECD countries are in the same cone. We verify the robustness of these findings in various ways. We use different data sets and adjust for international differences in productivity and human capital. We also investigate how aggregation, measurement error and factor intensity reversals affect our analysis. We confirm the endowment similarity for the OECD with skilled and unskilled labor data for a select group of rich OECD countries.

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Appendix A

A.1. Data from the Michigan model

The Michigan Model (see Deardorff and Stern, 1990) covers both developed and developing countries.[22] The data set provides data for 33 countries.[23] The list of countries and traded goods sectors that we use are reported in Tables A.1 and A.2. The labor data for the different sectors in each country are employment figures that are taken from the United Nations Industrial Statistics Yearbook and the International Labor Office's Yearbook of Labor Statistics.

The data on aggregate capital endowments of countries are based on the investment, exchange rate and investment deflator from the World Bank World Tables. The method for accumulating national investment flows to obtain national capital stocks is the perpetual inventory method (a depreciation rate of 13.3 percent is assumed). The stocks are valued in 1990 US dollars. The sector-level capital stocks for most countries were imputed. The imputation makes use of sector-level output data for the various countries and the sector-level capital–output ratio for Canada and the US from the respective input–output tables. Note that the capital–output ratios for a sector i in Canada (ca) and the U.S. (us) is defined as $(K_{\mathrm{ius}}+K_{\mathrm{ica}})/(Y_{\mathrm{ius}}+Y_{\mathrm{ica}})$. The latter measure is used in the Michigan Model to avoid that the imputation might involve country specific idiosyncrasies.

Gross output data for the 29 good sectors in the various countries are denominated in 1990 US dollars. The UNIS Yearbook and the United Nations Accounts Statistics (UNAS) Yearbook are the main sources. In cases of insufficient coverage, more disaggregated data (e.g. value added) are used to estimate gross output.

The exact procedure for the imputation of the sector-level capital stocks is as follows. First, each country's sectoral output is multiplied by the corresponding capital–output ratio of the US and Canada mentioned above. Next, these numbers are summed across sectors for each country. The obtained sum is then rescaled to match the aggregate estimates of the country's capital stock that was based on the World Bank investment flows (see above). Finally, the sectoral capital stock is obtained by rescaling the product that was used for the first step of the imputation (sectoral output times the Canadian–US capital–output ratio) with the same factor.

What is true for the UNIDO data is also true here: There is significant variation in the capital–labor ratios. Fig. A plots $K_{\mathrm{ic}}/K_{\mathrm{i}}$ versus $L_{\mathrm{ic}}/L_{\mathrm{i}}$ that should theoretically lie on the diagonal. Tables A1 and A2 provide the capital–labor ratios of the sectors and the countries that are covered, with and without the productivity adjustments and corrections for human capital. (All values are normalized vs. the relevant US overall endowment ratio.)

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[22] For a detailed description, we refer to the '1990 Michigan Model Database—Documentation.'

[23] We dropped Switzerland from the sample since its data were way out of line.

Table A.1

Country endowment ratios vs. the US

	Michigan		STAN		OECD	
	π_{lc}	π_{kc}	π_{hc}	π_{kc}	π_{kc}	$hskl_{\mathrm{c}}$
ARG	0.23	1.28	0.68	0.15		
ALA	1.00	1.15	0.90	1.03	1.24	1.88
ATA	1.16	1.67	0.67	1.03	0.40	
BLX	0.91	1.28	0.84	1.58	0.67	
BRZ	0.38	1.21	0.48	0.19		
CND	1.14	1.06	0.91	1.02	0.77	
CHL	0.21	0.53	0.66	0.08		
COL	0.27	0.57	0.54	0.08		
DEN	1.03	1.61	0.91	1.04	1.36	
FIN	0.79	1.74	0.86	1.42	0.82	1.22
FRA	0.67	1.33	0.67	1.35	0.63	1.30
GER	0.96	1.33	0.80	0.84	1.08	1.37
GRC	0.56	1.17	0.68	0.37		
HKG	0.64	1.40	0.74	0.42		
IND	0.15	0.49	0.45	0.01		
IRE	0.82	1.25	0.77	1.20		
ISR	0.46	1.23	0.85	0.78		
ITA	0.91	1.39	0.65	1.12	0.62	0.69
JPN	1.02	1.51	0.80	1.47	0.70	0.87
KOR	0.58	0.92	0.76	0.35		
MEX	0.34	0.81	0.54	0.13		
NTL	1.04	1.51	0.80	1.21	0.66	
NZA	0.84	0.98	1.02	0.88	1.01	1.90
NOR	0.87	1.72	0.91	1.27	0.92	
POR	0.35	1.17	0.50	0.29		
SNG	0.50	1.35	0.55	0.79		
SPA	0.83	1.11	0.61	0.93		
SWD	1.02	1.67	0.85	1.33	1.06	
TWN	0.61	0.92	0.70	0.33		
TRK	0.47	0.63	0.47	0.07		
UK	1.16	1.43	0.81	0.88	1.31	0.45
US	1.00	1.00	1.00	1.00	1.00	1.00
VEN	0.43	0.55	0.59	0.18		

π_{lc}: labor productivity difference, proxied by wage *n* country *c* vs. the US—Penn World Yearbook of Labor Statistics.

π_{kc}: capital productivity difference proxied by return to capital *n* country *c* vs. the US—Penn World.

π_{hc}: human capital vs. the US, proxied by returns to education (Hall and Jones, 1999).

K_{c}: the capital labor ratio vs. the US, unadjusted, Michigan model and STAN.

$hskl_{\mathrm{c}}$: ratio of high-skilled vs. low-skilled labor vs. the US: high-skill white-collar workers vs. others (OECD).

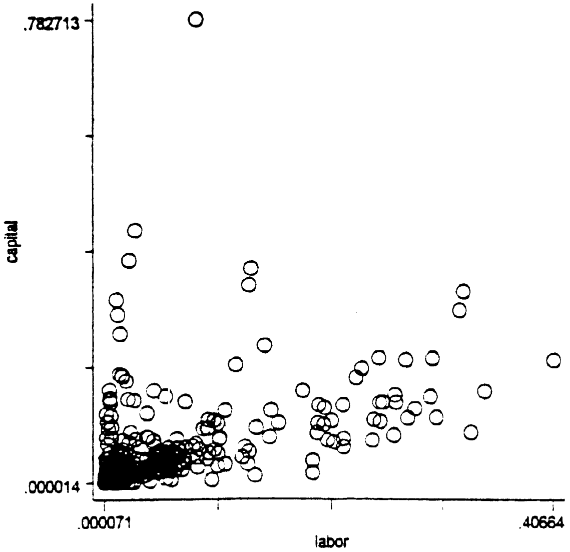

Fig. A. (A.1) Michigan, country share in sectoral capital vs. labor. (A.2) STAN, country share in sectoral capital vs. labor. (A.3) OECD, country share in sectoral capital vs. labor.

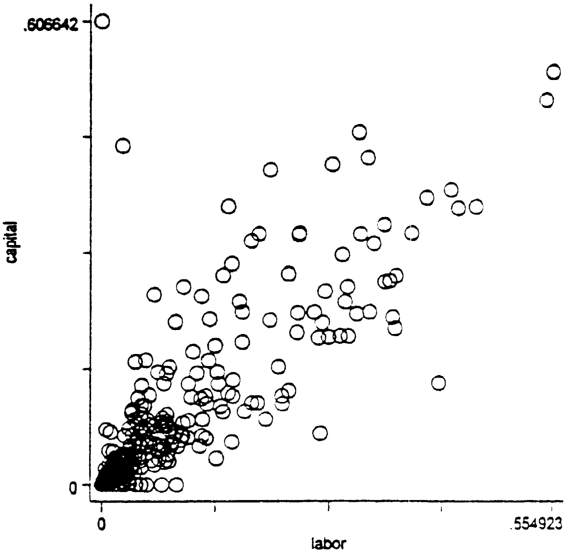

Fig. A. (*continued*)

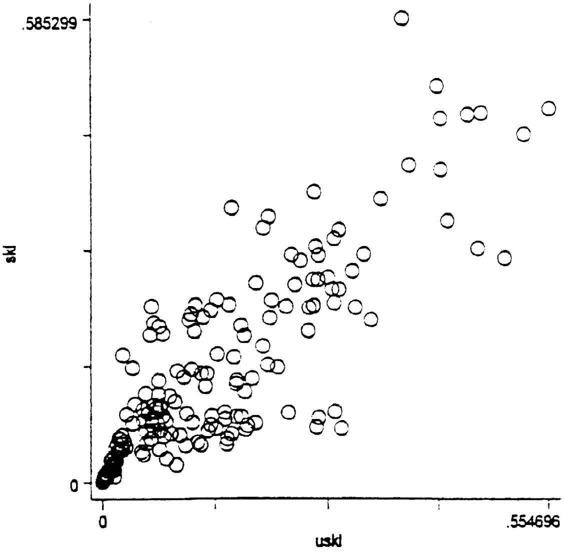

Fig. A. (*continued*)

A.2. STAN data

The STAN data that is published by the OECD provides internationally comparable manufacturing data at the sector level. We take the data for the US, the UK, France, Germany, the Netherlands, Belgium, Finland, Denmark, Norway, Sweden, Japan, Italy, Australia and Austria. The STAN database covers 28 manufacturing sectors that are reported in Table 2. Note that a few of the sectors are 4-digit, but most are 3-digit SIC industries. The year of the data that we choose for our analysis is 1990. The capital stocks are computed from sectoral investment flows with the perpetual inventory method. (The depreciation rate that is used is 13.3 percent). The capital stocks are valued in 1990 US dollars. The gross investment deflator of the US is used in the implementation and the foreign currency values are converted to 1990 US dollars with PPP values for investment goods. The labor data are the number of workers employed. Tables A.1 and A.2 report the sector-level capital–labor ratios with respect to the U.S., before and after productivity and human capital corrections. The factor prices and human capital measures are from the same sources discussed in 4.2.

A.3. Skilled versus unskilled labor

Internationally comparable data on different skill levels are hard to find. The OECD has made such data available for a number of countries (Australia, Finland,

Table A.2

Sectoral factor use ratios normalized by US endowment ratios

OECD high-skill vs. low-skill ratio*		STAN OECD capital–labor ratio				Michigan Model capital–labor ratio			
	$hskl_i$		k_i	k_i prod. adj.	k_i human cap.adj.		k_i	k_i prod. adj.	k_i human cap.adj.
1000 Agriculture, forestry and fishing	0.07	311 Food	0.92	1.08	0.92	100 Agriculture	0.10	0.60	0.21
2000 Mining	0.18	313 Beverages	2.61	3.08	2.61	310 Food	0.48	1.07	0.74
3100 Food, drink and tobacco	0.13	314 Tobacco	3.93	4.59	3.96	321 Textile	0.27	0.73	0.45
3200 Textile, leather and footwear	0.11	321 Textiles	0.69	0.82	0.69	322 Clothing	0.10	0.17	0.13
3300 Wood, cork and furniture	0.12	322 Wearing apparel	0.16	0.19	0.16	323 Leather	0.17	0.37	0.26
3400 Paper, printing and publishing	0.28	323 Leather and products	0.53	0.65	0.54	324 Footwear	0.11	0.26	0.18
3512X Basic chemicals	0.35	324 Footwear	0.29	0.37	0.30	331 Wood products	0.15	0.27	0.21
3522 Pharmaceuticals	0.57	331 Wood products	0.62	0.70	0.61	332 Furniture	0.05	0.08	0.06
3530 Petroleum refineries	0.31	332 Furnitures and fixtures	0.46	0.53	0.46	341 Paper	1.46	2.52	1.99
3550 Rubber products	0.15	341 Paper and products	2.26	2.57	2.22	342 Printing	0.53	0.82	0.67
3600 Stone, clay and glass	0.13	342 Printing and publishing	0.76	0.85	0.75	35A Chemicals	1.60	3.25	2.38
3710 Ferrous metals	0.14	351 Industrial chemicals	3.71	4.35	3.73	35B Petroleum products	2.39	5.50	3.65
3720 Non-ferrous metals	0.15	352 Other chemicals	1.49	1.74	1.50	355 Rubber products	0.55	1.05	0.79
3810 Fabricated metal products	0.15	353 Petroleum refineries	10.87	12.40	10.99	36A Minerals	0.81	1.81	1.26
382X Other non-electrical machinery	0.23	354 Petroleum and coal products	1.75	1.92	1.71	362 Glass products	0.88	1.80	1.32
3825 Computers and office equipment	0.41	355 Rubber products	1.25	1.47	1.27	371 Iron and steel	1.28	3.06	2.03
383X Electrical equipment	0.24	356 Plastic products, etc.	0.91	1.05	0.91	372 Non-ferrous metals	1.75	3.57	2.67
3832 Electronic equipment	0.30	361 Pottery, china etc.	0.95	1.22	0.97	381 Metal products	0.62	1.03	0.83
3841 Shipbuilding	0.16	362 Glass and products	1.59	1.89	1.62	382 Non-electrical machinery	0.63	1.06	0.84
3842 Railroad equipment	0.13	369 Non-metallic products, etc.	1.41	1.65	1.39	383 Transport equipment	0.66	1.11	0.88
3843 Motor vehicles	0.16	371 Iron and steel	1.99	2.37	2.00	384 Misc. manufactures	0.83	1.42	1.13
3845 Aircraft	0.27	372 Non-ferrous metals	2.04	2.34	2.02	38A Mining	0.60	0.91	0.76
3850 Instruments	0.23	381 Metal products	0.75	0.89	0.75				
3900 Other manufacturing	0.20	382 Non-electrical machinery	0.90	1.05	0.89				
		383 Electrical machinery	1.19	1.41	1.18				
		384 Transport equipment	1.44	1.67	1.44				
		385 Professional goods	0.98	1.08	0.98				
		390 Other manufacturing	1.16	1.32	1.15				

$hskl_i$: high-skill white-collar vs. others; k_i prod. adj. k_i for labor and capital productivity differences; k_i human cap. adj.: k_i adjusted for human capital differences. For sources of adjustments: see Table A.l.

France, Germany, Italy, Japan, New Zealand, the UK and the US). Four skill categories are distinguished: white-collar and blue-collar high-skilled and low-skilled workers. First, we include only the white-collar high-skilled workers as skilled labor. The latter fall under the industry and occupational categories 10 (legislators, senior officials and managers), 20 (professionals) and 30 (technicians and associate professionals). All the workers in the other categories are then low-skilled labor. Note that we also use a broader definition of skill that also encompasses low-skilled white-collar workers (occupation categories 40 and 50). Tables A.1 and A.2 provide skilled–unskilled ratios for the various sectors and countries. Fig. 3b plots for all countries its share in a sector's skilled labor (SK_{lic}/SK_{li}) versus its share in a sector's unskilled labor ($USKL_{ic}/USKL_{i}$). Fig. 3b uses the narrow definition for skilled labor. The EXCEL files are readily available at www.oecd.org/dsti/sti/prod/sti_wp.htm, attached to the OECD STI Working paper 55.

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