

Cones of diversification in a model of international comparative advantage

John P. Burkett

University of Rhode Island, USA

Abstract

The hypothesis that all countries belong to a single cone of diversification is often used in studies of international trade. However, contrary to this hypothesis, the range of capital-labor input ratios in U.S. industries does not encompass the range of capital-labor endowment ratios in the world's economies. Furthermore, among countries with capital-labor endowment ratios below the range of U.S. capital-labor input ratios, wage rates are much lower than in the U.S. In this paper the one-cone hypothesis is assessed relative to a two-cone alternative by clustering countries with similar factor proportions, estimating regressions for gross national product and net exports, testing for equality of coefficients, and approximating the posterior odds on one- and two-cone models. Rejecting the one-cone hypothesis, the paper presents estimates of a two-cone model and considers their implications for factor flows and the prospects of emerging market economies.

Key words

international trade, cones of diversification.

Address for Correspondence

Department of Economics, University of Rhode Island, 10 Chafee Road, Suite 3,
Kingston, RI 02881, USA. E-mail: burkett@uriacc.uri.edu.

1. INTRODUCTION

In Heckscher-Ohlin trade theory, as is well known, there may exist one or more cones of diversification within which countries have similar factor proportions, identical factor prices, and identical sets of products. For countries falling within a cone of diversification, producing as many goods as they have factors, the theory predicts that net exports by commodity, as well as national income, are linear functions of factor endowments.

Because factor-price equalization wonderfully simplifies models, it is tempting to assume that all countries fall in a single cone. Although often used, the one-cone assumption is seldom assessed relative to multi-cone alternatives, perhaps for want of data on factor prices and product sets.¹ In this paper I assess the one-cone hypothesis by (1) comparing the range of capital-labor input ratios in U.S. industry with the range of capital-labor endowment ratios in the world's economies, (2) comparing wage data for countries with high and low capital-labor endowment ratios, and (3) clustering countries with similar factor proportions, estimating regressions for gross national product (GNP) and net exports, testing for equality of coefficients, and approximating the posterior odds on one- and two-cone models. Finally, I present estimates of the preferred model and consider their implications for factor flows and the prospects of emerging market economies.

2. INTENSITIES, ENDOWMENTS, AND WAGES

According to the one-cone hypothesis, factor intensities differ among industries more than factor endowments differ among countries—i.e., the range of factor input ratios encompasses the range of factor endowment ratios. To empirically assess this feature of the one-cone hypothesis, let us compare the range of capital-labor intensities found in U.S. industries at the four-digit SIC level (U.S. Bureau of the Census, 1976) to the range of capital-labor endowment ratios in a cross-section of countries (Leamer, 1984), both data sets pertaining to 1975. Capital per worker in U.S. industries ranges from \$1,270 for children's coats and suits (SIC 2363) to \$200,623 for petroleum refining (SIC 2911). Capital-labor endowment ratios lie within the indicated range for forty-three of Leamer's fifty-eight countries but beneath it for the other fifteen, suggesting that not all countries belong to the same cone. If industry data distinguished more factors, we might find more countries whose factor

endowment ratios fell outside the range of U.S. industries' factor intensities.

Under the one-cone hypothesis, all countries have the same factor prices. If consistent data on factor prices were available for many countries and factors, they could be used to identify diversification cones. However, given that they are available for only a few countries and factors, the best we can do is to compare for a few occupations the wage rates earned in the U.S. and in some of the fifteen countries with the lowest capital-labor ratios. The occupations for which country coverage is widest are hand compositors, machine compositors, printing press operators, and bookbinders. For these occupations, it is possible to compare wages, at purchasing power parity, in the U.S. and four of the fifteen countries with the lowest capital-labor endowment ratios: Mauritius, Nigeria, Paraguay, and the Philippines. From Table 1, it is apparent that wage rates are much higher in the U.S. than in the latter countries, again suggesting that not all countries fall in a single cone. Sparse though they are, the wage data help motivate an effort to cluster countries into cones using other, more comprehensive data.

Table 1 goes here.

3. COUNTRY CLUSTERS AND DIVERSIFICATION CONES

Lacking extensive cross-national data on factor prices and product assortment, I cluster countries with similar factor proportions. Data for eleven factors in fifty-eight countries in 1975 are taken from Leamer (1984). The factors are cumulated and discounted investment (CAPITAL), professional workers (LABOR1), non-professional but literate workers (LABOR2), illiterate workers (LABOR3), land in humid tropical areas (LAND1), land in dry areas (LAND2), land in humid mild areas (LAND3), land in humid cold areas (LAND4), primary solid fuels (COAL), ores and other minerals (MINERALS), and oil and gas (OIL).²

The width of a cone sets an upper limit on the angle between the factor vectors of countries belonging to the cone. The factor vectors of countries belonging to different cones are not so limited. Accordingly, the angle between factor vectors is a natural measure of dissimilarity and an appealing basis for cluster analysis.³

We cluster countries by a method known as partitioning around medoids (PAM). The method's originators, Kaufman and Rousseeuw (1990), describe it as follows:

In order to obtain k clusters, the method selects k objects (which

are called *representative objects*) in the data set. The corresponding clusters are then found by assigning each remaining object to the nearest representative object.... The representative objects must be chosen so that they are (in a certain sense) centrally located in the clusters they define. To be exact, the average distance (or average dissimilarity) of the representative object to all the other objects of the same cluster is being minimized. For this reason, such an optimal representative object we call the *mediod* of its cluster (p. 40).

PAM is attractive because it is more robust to outliers than are methods that minimize the sum of squared errors within clusters (Kaufman and Rousseeuw, 1990: 117).

While a country may fall either within or between theoretical cones of diversification, each country lies within some statistical cluster. Thus two statistical clusters, for example, could be interpreted as two cones or as one cone and a scattering of countries outside of the cone. To determine which interpretation is more accurate for a data set as small as ours would be difficult. In the remainder of this paper let us assume, for simplicity, that each country belongs to some cone.

When we request two clusters, PAM produces the partition shown in Table 2. The first cluster consists of twenty-six countries whose *mediod* is the Dominican Republic; the second comprises thirty-two countries whose *mediod* is France.

Table 2 goes here.

Alternative names for clusters one and two are suggested by a couple of striking features of their factor proportions, as shown in Table 3. First, GNP per worker, CAPITAL per worker, and LABOR1 per worker are much lower, on average, in cluster one than in cluster two. Thus we may refer to cluster one as “poor” and cluster two as “rich.” (We should bear in mind, however, that these labels are based on comparisons of averages across cones, not pairwise comparisons of countries. In fact, the maximum values of GNP per worker, CAPITAL per worker, and LABOR1 per worker in cluster one exceed the minimum values in cluster two.) Second, the pattern of land per worker differs sharply between clusters. Cluster one has sixteen times more tropical land (LAND1) per worker than cluster two but has no land in the cold humid zone (LAND4). Thus it is tempting to call cluster one “south” and cluster two “north.” However, this usage could be misleading because Argentina, Australia, and New Zealand are members of cluster two. A more accurate

Table 3 goes here.

though less pithy geographic designation for the two cones is “tropical” and “non-tropical.”

The s statistic, values of which are shown in Table 2, is a measure of how securely a country is classified. It is defined as follows:

$$s = \frac{b - a}{\max(a, b)},$$

where a is the average dissimilarity of the country to other countries in its cluster and b is the average dissimilarity of the country to countries in the other cluster. (Dissimilarity, recall, is measured as the angle between factor vectors. Angles are expressed in radians.) The statistic s can range from -1 (worst) to 1 (best). For our sample, s ranges from -.03 (Libya) to .45 (Dominican Republic). The average values of s are .28 for cluster one and .24 for cluster two. The average dissimilarity between countries in cluster one and their mediod (Dominican Republic) is .69, while that between countries in cluster two and their mediod (France) is .77. The separation between clusters (minimum angle between a country in cluster one and a country in cluster two) is .57.

When PAM is asked for three clusters, it picks the Dominican Republic, Ireland, and Japan as medioids. Clustered around the Dominican Republic are twenty-four countries (all of which were so clustered when two groups were requested). Clustered about Ireland are thirteen countries (two drawn from the old cluster one and eleven from the old cluster two). Grouped around Japan are twenty-one countries (all of which belonged to old cluster two). Unfortunately, GNP and net export equations estimated for cluster two would have only one degree of freedom (thirteen observations minus twelve coefficients). One degree of freedom is plainly inadequate as a basis for the asymptotic tests employed below. Hence the remainder of the paper focuses on models with only one or two clusters.

4. MODEL SELECTION

For purposes of choosing between one- and two-cone models, we can use classical tests for equality of coefficients or a Bayesian model selection procedure based on a posterior odds ratio. The classical approach can be implemented using a dummy variable in likelihood ratio or Wald tests. Letting D equal 1 for countries in the poor (tropical) cluster and 0 for countries in the rich (non-tropical) cluster, we can define ten new variables: $DCAPITAL = D \cdot CAPITAL$,

DLABOR1 = D·LABOR1, DLABOR2 = D·LABOR2, DLABOR3 = D·LABOR3, DLAND1 = D·LAND1, DLAND2 = D·LAND2, DLAND3 = D·LAND3, DCOAL = D·COAL, DMINERALS = D·MINERALS, AND DOIL = D·OIL. (Because countries in the poor cluster have no LAND4, we have no need for the product of that variable and D.)

Both likelihood ratio and Wald approaches involve regressing GNP and the ten net export variables on a constant, the eleven resource variables, D, and the ten products just defined and testing the null hypothesis that the coefficients of D and the ten products are zero in all equations. Excluding eleven variables from eleven equations amounts to imposing 121 restrictions. In the likelihood ratio test, the $\chi^2(121)$ statistic is 547.6, with a marginal significance level of $1.5 \cdot 10^{-55}$, strongly rejecting the null hypothesis. However, this test may be regarded with some skepticism because it makes no allowance for heteroskedasticity, evidence of which is reported by Leamer (1984).

To allow for heteroskedasticity, we can use Wald tests based on consistent estimates of covariance matrices, as proposed by White (1980). In this approach, a test of the hypothesis that the coefficients of D and the ten products are zero in any given equation is based on a $\chi^2(11)$ statistic and that of the hypothesis that those coefficients are zero in all eleven equations is based on a $\chi^2(121)$ statistic. These statistics are shown in Table 4. Their marginal significance levels range from $3.4 \cdot 10^{-10}$ for LAB to vanishingly small quantities for PETRO and the eleven equations as a whole.⁴

Table 4 goes here.

The results thus far can be summarized by saying that the one-cone hypothesis is rejected by classical tests of conventional size. A shortcoming of such a test is that its size is fixed at an arbitrary value while its power under the alternative hypothesis grows with sample size. Given enough observations, such a test is almost sure to reject any sharp hypothesis (Leamer, 1978).

To avoid these problematic aspects hypothesis testing, we can consider model selection based on a posterior odds ratio. When the sample information dominates the prior information, selecting the model favored by the posterior odds ratio is equivalent to a model selection procedure proposed by Schwarz (1978)—namely, to choose the model with the greatest value of the criterion

$$M \cdot N^{-k/2},$$

where M is the maximum of the likelihood function, N is the sample size,

and k is the number of coefficients.⁵ The maximum of the concentrated likelihood function for a homoskedastic multivariate regression is given by Cramer (1986) as

$$M = C \cdot |\widehat{\Sigma}|^{-N/2},$$

where C is a constant that does not depend on the number of parameters and $\widehat{\Sigma}$ is the estimated covariance matrix of disturbances. (We ignore possible heteroskedasticity in the following calculations.) Substituting the last equation into the preceding expression and dropping the constant, we see that Schwarz's selection procedure for a multivariate regression amounts to choosing the model with the largest value of the following statistic:

$$SC = |\widehat{\Sigma}|^{-N/2} N^{-k/2}.$$

Because the value of $|\widehat{\Sigma}|$ is influenced by the scaling of the variables, we standardize the variables to zero mean and unit variance before computing SC for either model. (Having standardized the variables, we drop the constant term from the regressions.) The values of $\ln(SC)$ for the one- and two-cone models are 717.87 and 720.49.

Letting SC_i denote the value of SC for a model with i cones, we form the ratio $\Lambda = SC_2/SC_1$, a multivariate generalization of the asymptotic Bayes factor used by Bowen et al. (1987). In our case, Λ takes the value 13.71, which we interpret to mean that our posterior odds in favor of the two-cone model should be about 13.71 times as great as our prior odds. In short, the data seem to strongly favor the two-cone model over the one-cone model.

5. ESTIMATES OF A MODEL WITH TWO CONES OF DIVERSIFICATION

OLS estimates of the GNP and net export equations for the countries in clusters one (poor) and two (rich) appear in Tables 5a and 5b. Weighted least squares estimates are not reported here because there is no need for them: While OLS residual variances differ between clusters, within clusters there is no evidence of heteroskedasticity of the form found by Leamer in residuals from equations estimated using data pooled across clusters. Indeed, the heteroskedasticity found in the pooled estimates may be merely symptomatic of more general parameter shifts between clusters.

Table 5a goes here.

Table 5b goes here.

The coefficients of the GNP equation may be interpreted as marginal products; hence the plausibility of estimates of these coefficients is easily checked. On this score there is good news and bad news. The good news is that when comparing the estimates for the two clusters, we see evidence that the rich cluster has a lower marginal product of CAPITAL and a higher marginal product of LABOR3. This pattern is consistent with the differences in factor proportions reported in Table 3. The bad news is that there are five implausible negative estimated coefficients (one in the equation for poor countries and four in the equation for rich countries).

The plausibility of the estimates of the net export equations is more difficult to assess. Nonetheless, it is reassuring that in cluster one OIL, MINERALS, LAND2, and LABOR2 seem to confer a comparative advantage in PETRO, MAT, ANL, and LAB respectively. Also comforting is the appearance in cluster two that LAND3, LABOR2, and CAPITAL confer comparative advantage in CER, LAB, and CAP respectively. However, it is disturbing to see in cluster one a negative and significant coefficient on CAPITAL in the CAP equation.

The OLS estimates are suspect not only because they conflict with prior beliefs about some coefficients, but also because they are highly sensitive to errors in variables, as Leamer (1984) found by computing reverse regressions. In an effort to obtain estimates that make use of prior information about coefficients and are less sensitive to errors in variables, we follow Leamer (1984) in computing Bayesian posterior mean estimates. Prior means for the coefficients are shown in Tables 6a and 6b.

Table 6a goes here.

The prior means for the coefficients of the GNP equation are based on beliefs about factor prices, which are presumed to reflect marginal products. We elicit such beliefs in the manner of Leamer (1984) but distinguish poor and rich countries. Under competitive conditions and absent taxes, the coefficient of CAPITAL should represent the sum of the real interest rate and the depreciation rate. Following Leamer, we assume a 13.3% depreciation rate and—for the rich countries—a real interest rate of about 3.7%. Bearing in mind that CAPITAL is expressed in millions and GNP in thousands, we arrive at a prior mean of 170.⁶ For the poor countries, we assume a real interest rate of about 6.7% and set the prior mean for the coefficient of CAPITAL at 200. The prior standard errors are set equal to the prior means, indicating considerable uncertainty.

Table 6b goes here.

The prior means for the coefficients of labor variables are based on wages in a poor country (Brazil) and a rich country (Netherlands).⁷ Wage rates in domestic currency are taken from the International Labour Organisation's

October 1975 inquiry (ILO, 1976) and converted into dollars at purchasing power parities obtained from the Penn World Table (Summers and Heston 1991). LABOR1 is represented by one of the highest paid categories of workers, outside electrical fitters. LABOR2 is represented by a moderately paid and presumably literate group, hand compositors in the printing industry. LABOR3 is represented by one of the lowest paid groups, unskilled laborers employed by manufacturers of machinery. The wages for each group are more than twice as high in the Netherlands as in Brazil. The ratio of the wages of electrical fitters to unskilled workers is slightly higher in Brazil than in the Netherlands, as might be expected. The prior standard errors are set equal to one-half the prior means, indicating confidence that the coefficients are non-negative.

The prior means for the coefficients of land variables are based on rents. Lacking any information about rents outside the United States, we take the prior means directly from Leamer (1984). These are based on U.S. Department of Agriculture data on rents for LAND3 and LAND4 and guesses about rents on LAND1 and LAND2. For the rich countries, we adopt Leamer's prior standard errors: one-quarter the prior mean for LAND3, one-half the prior mean for LAND4, and twice the prior means for LAND1 and LAND2. For the poor countries, we set all prior standard errors equal to twice the prior means, signifying great uncertainty.

To elicit prior means for the coefficients of subterranean resources (COAL, MINERALS, OIL), we reason as follows: The resource endowments are proxied by extraction, measured in thousands of dollars. At one extreme, when extraction uses no land, labor, or capital, a dollar's worth of resources extracted adds a dollar to GNP. In this case the coefficient of COAL, MINERALS, and OIL should all be 1.0. At the opposite extreme, extraction from marginal deposits yields no rent. In that case the coefficient of each resource should be zero. Splitting the difference, we set the prior mean for the coefficient of each subterranean resource equal to 0.5.⁸ We set the prior standard errors equal to .25, indicating confidence that the coefficients are between zero and one.

In specifying prior distributions for the coefficients of the net export equations, we follow the approach suggested by Leamer (1984): An increase in a country's endowment of a resource raises consumption of each good by the product of the effect on GNP and the share of the good in expenditure (taken to equal GNP on the assumption that trade is balanced). Assuming that half of expenditure falls on non-traded goods and services and the other half is

evenly divided among the ten trade aggregates, we set the expenditure shares for each trade aggregate to $1/20$. Thus an increase in a resource endowment is assumed to raise consumption of each aggregate by $1/20$ of the increase in GNP. For industries that are not major users of a resource, we presume the production effect of an increase in the resource is negligible.⁹ In these cases the total effect of an increase in a resource is simply the consumption effect just described. For industries which are major users of a resource, the effects on net exports are taken to be positive, equal, and large enough to leave the aggregate trade balance unaffected. Thus columns (excluding entries in the GNP rows) in Table 6 sum to zero. (For details, see Leamer, 1984: 146-50.) The signs of the prior means are the same for poor and rich countries; only the magnitudes differ. The prior standard errors for coefficients of the trade equations are all set equal to the corresponding prior means, indicating considerable uncertainty.

Posterior means for the coefficients are shown in Tables 7a and 7b.¹⁰ Some of the differences between these estimates and their OLS counterparts in Table 5 are worthy of mention. Starting with the equations for poor countries, we note that in the equation for TROP, the posterior mean of the coefficient of LAND1 is significantly greater than zero. The posterior mean of the coefficient of CAPITAL in the equation for CAP has the expected positive sign, although it is insignificant. Turning to the equations for the rich countries, we note that in the GNP equation, the posterior mean of the coefficient of LAND2 has the theoretically valid positive sign. The posterior means of the effects of OIL on PETRO, MINERALS on MAT, and LAND4 on FOR are all significantly greater than zero. In general, the posterior means appear more plausible than their OLS counterparts, as might be expected.

The effect of increases in a resource on net exports can differ in sign from one cone to another. Some evidence of such differences can be seen by comparing the posterior means of the trade equations for poor and rich countries. Although the prior means have the same signs for poor and rich countries, some posterior means are significantly greater than zero for poor countries but significantly less than zero for rich countries or vice versa. In the first category are the estimated effects of LABOR2 on FOR and CER and of CAPITAL on TROP. In the second category are the estimated effects of LABOR1 on CER and CAPITAL on MACH. (For graphic evidence of a non-monotonic effect of CAPITAL on MACH, see Figure C.9a in Leamer 1984.)

Table 7a goes here.

Table 7b goes here.

6. CONCLUSIONS, RESEARCH PROBLEMS, AND POLICY IMPLICATIONS

As of 1975 there appear to have been at least two cones of diversification, one including twenty-six mostly poor countries and another embracing thirty-two mostly rich countries. Estimated marginal products differ between cones in a plausible manner, such that capital flows from rich to poor countries and emigration of unskilled workers from poor to rich countries should raise world output. Thus resource endowments appear to have differed among countries so much that factor price differences could withstand the leveling effects of trade and serve as an incentive to factor flows.

The existence of more than one cone of diversification complicates the task of predicting the production and trade patterns of emerging market economies such as the former centrally planned economies. An appropriate procedure would be to update the clustering of existing market economies, assign emerging market economies to appropriate cones based on angles between resource vectors, and use equations estimated for the appropriate cones to predict the production and trade patterns of the cones' new members.

Although the transition to markets is motivated by hopes of replicating the performance of rich capitalist economies, we cannot yet dismiss the possibility that some of the transitional economies may find themselves in a low-income cone of diversification. Afghanistan, at least, appears to have been there before its brief experiment with socialism. Policy makers in transitional economies belonging to a low-income cone face a delicate task of making efficient use of their existing resources while simultaneously fostering the accumulation of the physical and human capital needed to join a more prosperous cone.

Table 1: Hourly Wages of Adult Earners, October 1975

Country	Hand Compositors	Machine Compositors	Printing Press Operators	Bookbinders
Mauritius	1.08	-	0.84	0.89
Nigeria	0.59	0.59	0.59	0.59
Paraguay	1.22	1.01	0.84	0.84
Philippines	0.58	0.53	0.59	0.49
U.S.	6.51	6.51	6.51	6.79

Wages are expressed here in U.S. dollars at purchasing power parity. They were derived by dividing wages in local currencies (ILO, 1976) by purchasing power parity exchange rates (Summers and Heston, 1991).

**Table 2: Clusters Based on
Angles Between Factor Vectors**

Cluster One		Cluster Two	
Country	<i>s</i>	Country	<i>s</i>
Afghanistan	.11	Argentina	.24
Brazil	.41	Australia	.02
Burma	.42	Austria	.31
Chile	.21	Belgium-Luxemb.	.36
Colombia	.42	Canada	.11
Costa Rica	.38	Cyprus	.25
<i>Dominican Rep.^a</i>	.45	Denmark	.38
Ecuador	.43	Finland	.17
Egypt	.05	<i>France^a</i>	.39
El Salvador	.32	Germany, West	.30
Ghana	.44	Greece	.29
Honduras	.44	Hong Kong	.16
India	.17	Iceland	.25
Indonesia	.39	Ireland	.29
Jamaica	.08	Israel	.19
Liberia	.22	Italy	.36
Malaysia	.22	Japan	.34
Mauritius	.18	Korea, South	.09
Mexico	.20	Libya	-.03
Nigeria	.26	Malta	.23
Panama	.41	Netherlands	.34
Paraguay	.03	New Zealand	.27
Peru	.38	Norway	.28
Philippines	.21	Portugal	.25
Sri Lanka	.21	Singapore	.23
Thailand	.34	Spain	.35
		Sweden	.17
		Switzerland	.30
		Turkey	.08
		United Kingdom	.25
		United States	.21
		Yugoslavia	.19

^a Mediod of cluster.

Table 3
Means of Selected Ratios
for Clusters One and Two

Ratio	Cluster One	Cluster Two
GNP/LABOR ^a	1464.65	9727.25
CAPITAL/LABOR	1.5893	16.1974
LABOR1/LABOR	0.0496	0.1085
LABOR2/LABOR	0.5468	0.7960
LABOR3/LABOR	0.4036	0.0956
LAND1/LABOR	7.4720	0.4655
LAND2/LABOR	1.4495	13.1868
LAND3/LABOR	0.9292	4.3769
LAND4/LABOR	0.0000	3.7993
COAL/LABOR	2.3425	46.7129
MINERALS/LABOR	66.9028	57.0314
OIL/LABOR	44.4674	456.0720

^aLABOR = LABOR1 + LABOR2 + LABOR3.
LABOR is expressed in thousands of workers.
GNP is expressed in thousands of dollars.
CAPITAL is expressed in millions of dollars.

Table 4
 χ^2 Statistics for Wald Tests

Dependent Variable(s)	Degrees of Freedom n	$\chi^2(n)$
GNP	11	941.4
PETRO	11	4141.5
MAT	11	689.6
FOR	11	158.5
TROP	11	644.6
ANL	11	124.3
CER	11	1035.4
LAB	11	67.7
CAP	11	778.4
MACH	11	390.4
CHEM	11	159.6
All	121	9131.3

Table 5a: OLS Estimates of GNP and Net Export Equations for Poor Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LABOR4	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL	R ²
GNP ^a	523.	2450.	255.	-158.	40.1	46.5	64.9	.	4.65	2.46	1.35	1.35	.996
	9.2 ^b	0.57	1.5	-0.74	3.7	2.3	0.52	.	0.58	1.4	3.0	3.0	
PETRO	-28.8	-145.	-12.0	38.2	-0.649	-7.83	0.846	.	-1.13	0.201	0.966	0.966	.999
	-11.6	-0.77	-1.6	4.1	-1.4	-8.7	0.15	.	-3.2	2.7	48.0	48.0	
MAT	-2.92	114.	-7.05	5.94	-0.321	-2.13	-2.27	.	-0.289	0.713	-0.029	-0.029	.989
	-4.0	2.1	-3.2	2.2	-2.3	-8.2	-1.4	.	-2.8	33.0	-5.0	-5.0	
FOR	-2.39	324.	1.43	-6.20	-0.671	-2.98	1.90	.	-0.373	0.212	-0.025	-0.025	.609
	-0.71	1.3	0.14	-0.50	-1.1	-2.5	0.26	.	-0.79	2.1	-0.94	-0.94	
TROP	19.4	305.	5.52	-6.76	0.353	-5.53	-15.2	.	-0.068	-0.201	-0.0861	-0.0861	.918
	3.7	0.77	0.35	-0.35	0.36	-2.9	-1.3	.	-0.092	-1.3	-2.0	-2.0	
ANL	-0.927	-237.	14.4	-8.31	0.607	1.58	0.855	.	0.652	-0.104	0.0222	0.0222	.839
	-0.80	-2.7	4.1	-1.9	2.8	3.8	0.34	.	4.0	-3.0	2.4	2.4	
CER	15.3	-674.	27.4	21.2	0.329	-2.79	-1.58	.	-0.692	0.106	-0.040	-0.040	.925
	3.7	-2.2	2.2	1.4	0.42	-1.9	-0.17	.	-1.2	0.86	-1.2	-1.2	
LAB	0.218	-260.	16.4	7.06	0.716	1.41	-0.325	.	-0.029	-0.071	-0.060	-0.060	.965
	0.21	-3.4	5.3	1.9	3.7	3.8	-0.15	.	-0.20	-2.3	-7.4	-7.4	
CAP	-8.38	-203.	7.93	-27.0	0.433	4.23	2.13	.	1.80	-0.100	-0.053	-0.053	.987
	-5.6	-1.8	1.7	-4.8	1.5	7.8	0.64	.	8.5	-2.2	-4.4	-4.4	
MACH	-36.7	-244.	-9.64	-39.4	1.86	4.71	4.01	.	3.00	-0.075	-0.116	-0.116	.979
	-8.1	-0.71	-0.70	-2.3	2.2	2.9	0.40	.	4.7	-0.55	-3.2	-3.2	
CHEM	-6.14	-188.	-6.70	-15.1	-0.445	-0.008	2.34	.	1.08	0.0095	0.0162	0.0162	.932
	-1.7	-0.70	-0.63	-1.1	-0.66	-0.01	0.30	.	2.1	0.089	0.56	0.56	

^aGNP is measured in thousands of dollars, CAPITAL in millions.

^bt-statistics appear beneath estimated coefficients.

Table 5b: OLS Estimates of GNP and Net Export Equations for Rich Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL	R ²
GNP ^a	471.	13019.	-1108.	1585.	-997.	-68.5	94.7	-167.	7.52	29.3	1.63	.999
	18.	2.2	-2.4	1.6	-0.99	-0.78	1.7	-2.8	3.4	2.1	0.89	
PETRO	-9.00	-145.	-222.	-5.99	-216.	41.6	-8.38	9.48	0.287	-0.728	-0.184	.994
	-4.0	-0.28	-5.5	-0.071	-2.5	5.5	-1.7	1.8	1.5	-0.59	-1.2	
MAT	-1.73	419.	-212.	148.	45.1	-3.13	5.49	6.26	0.437	0.121	0.0795	.959
	-0.75	0.80	-5.2	1.7	0.51	-0.41	1.1	1.2	2.3	0.097	0.50	
FOR	1.30	-601.	-62.5	-12.4	-226.	10.2	-4.97	-14.2	-0.062	4.29	-0.259	.793
	0.43	-0.87	-1.2	-0.11	-1.9	1.0	-0.76	-2.0	-0.24	2.6	-1.2	
TROP	-5.70	799.	-4.97	76.8	91.6	-12.7	5.40	-6.42	-0.92	0.44	0.29	.950
	-3.9	2.4	-0.19	1.4	1.6	-2.6	1.7	-1.9	-7.4	0.56	2.9	
ANL	5.01	98.3	-153.	147.	126.	-13.5	8.43	1.19	-0.448	-0.818	0.312	.456
	1.04	0.090	-1.8	0.83	0.68	-0.83	0.81	0.11	-1.1	-0.31	0.93	
GER	0.33	1150.	-238.	196.	99.0	-18.1	20.6	-6.66	-0.414	0.878	0.511	.989
	0.18	2.7	-7.2	2.9	1.4	-2.9	5.2	-1.6	-2.6	0.88	4.0	
LAB	-9.8	444.5	208.2	-1.81	162.	-18.8	-0.382	-1.90	-0.870	-0.767	0.353	.747
	-2.2	0.45	2.7	-0.011	0.97	-1.28	-0.041	-0.19	-2.4	-0.33	1.2	
CAP	16.2	-2746.	240.	-85.8	20.2	4.75	-9.86	5.92	0.224	-1.52	-0.167	.945
	4.7	-3.5	3.9	-0.67	0.15	0.41	-1.3	0.73	0.76	-0.81	0.69	
MACH	52.0	-5696.	42.2	-171.	-387.	53.9	-15.3	13.3	3.83	-2.57	-1.42	.963
	6.6	-3.2	0.30	-0.59	-1.3	2.0	-0.90	0.72	5.7	-0.60	-2.6	
CHEM	10.9	-210.	-128.	50.5	112.	-2.28	-1.02	14.4	0.657	-3.19	0.0469	.890
	4.5	-0.38	-3.0	0.57	1.2	-0.28	-0.20	2.6	3.2	-2.5	0.28	

^aGNP is measured in thousands of dollars, CAPITAL in millions.

^bt-statistics appear beneath estimated coefficients.

Table 6a: Prior Means for Coefficients of Equations for GNP and Net Exports for Poor Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL
GNP ^a	200.0	2320.0	2140.0	834.0	10.0	5.0	100.0	.	0.5	0.5	0.5
PETRO	-10.0	-116.0	-107.0	-41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	0.1
MAT	-10.0	-116.0	-107.0	-41.7	-0.5	-0.25	-5.0	.	0.225	0.225	0.1
FOR	-10.0	-116.0	26.75	41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	-0.025
TROP	-10.0	-116.0	26.75	41.7	2.0	0.583	11.67	.	-0.025	-0.025	-0.025
ANL	-10.0	-116.0	26.75	41.7	-0.5	0.583	11.67	.	-0.025	-0.025	-0.025
CER	-10.0	-116.0	26.75	41.7	2.0	0.583	11.67	.	-0.025	-0.025	-0.025
LAB	15.0	-116.0	26.75	41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	-0.025
CAP	15.0	-116.0	26.75	-41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	-0.025
MACH	15.0	464.0	26.75	-41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	-0.025
CHEM	15.0	464.0	26.75	-41.7	-0.5	-0.25	-5.0	.	-0.025	-0.025	-0.025

^aGNP is measured in thousands of dollars, CAPITAL in millions.

Table 6b: Prior Means for Coefficients of Equations for GNP and Net Exports for Rich Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL
GNP ^a	170.0	6720.0	5460.0	2780.0	10.0	5.0	100.0	50.0	0.5	0.5	0.5
PETRO	-8.5	-336.0	-273.0	-139.0	-0.5	-0.25	-5.0	-2.5	-0.025	-0.025	0.1
MAT	-8.5	-336.0	-273.0	-139.0	-0.5	-0.25	-5.0	-2.5	0.225	0.225	0.1
FOR	-8.5	-336.0	68.25	139.0	-0.5	-0.25	-5.0	10.0	-0.025	-0.025	-0.025
TROP	-8.5	-336.0	68.25	139.0	2.0	0.583	11.67	-2.5	-0.025	-0.025	-0.025
ANL	-8.5	-336.0	68.25	139.0	-0.5	0.583	11.67	-2.5	-0.025	-0.025	-0.025
CER	-8.5	-336.0	68.25	139.0	2.0	0.583	11.67	10.0	-0.025	-0.025	-0.025
LAB	12.75	-336.0	68.25	139.0	-0.5	-0.25	-5.0	-2.5	-0.025	-0.025	-0.025
CAP	12.75	-336.0	68.25	-139.0	-0.5	-0.25	-5.0	-2.5	-0.025	-0.025	-0.025
MACH	12.75	1344.0	68.25	-139.0	-0.5	-0.25	-5.0	-2.5	-0.025	-0.025	-0.025
CHEM	12.75	1344.0	68.25	-139.0	-0.5	-0.25	-5.0	-2.5	-0.025	-0.025	-0.025

^aGNP is measured in thousands of dollars, CAPITAL in millions.

Table 7a: Posterior Means of Coefficients of GNP and Net Export Equations for Poor Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL	R^2
GNP ^a	592.0	2709.0	282.	-55.8	34.5	15.7	-16.6	.	0.487	0.557	0.791	.994
	14.1 ^b	2.5	3.1	-0.83	4.9	1.8	-0.18	.	1.9	2.3	4.2	
PETRO	-36.3	-284.	-4.06	18.3	0.92	-0.967	-0.311	.	-0.032	-0.018	0.994	.991
	-20.5	-3.0	-0.83	5.2	3.4	-4.1	-0.088	.	-1.3	-0.76	80.2	
MAT	-4.02	2.44	-3.09	6.51	-0.018	-1.13	-2.18	.	-0.167	0.696	-0.021	.977
	-6.0	0.052	-1.6	2.7	-0.15	-6.3	-1.5	.	-1.8	32.6	-3.8	
FOR	-1.86	-58.3	17.5	-2.31	0.068	-0.352	-2.24	.	-0.027	-0.012	-0.012	.347
	-0.85	-0.58	3.0	-0.59	0.21	-1.5	-0.57	.	-1.1	-0.51	-0.86	
TROP	7.89	-144.	20.5	-0.649	1.58	0.090	0.727	.	-0.025	-0.030	-0.038	.847
	2.2	-1.3	2.6	-0.11	2.6	0.16	0.097	.	-0.99	-1.2	-2.1	
ANL	0.799	-177.	12.6	2.48	0.053	1.01	2.65	.	-0.012	-0.040	-0.004	.643
	0.80	-2.6	4.4	1.0	0.31	3.1	1.1	.	-0.50	-2.0	-0.59	
CER	6.24	-246.	13.7	-6.2	1.2	-0.005	3.62	.	-0.026	-0.022	-0.028	.868
	2.1	-2.4	2.0	-1.2	2.3	-0.010	0.55	.	-1.0	-0.89	-1.8	
LAB	1.55	-149.	12.5	3.97	0.373	0.230	-0.460	.	-0.027	-0.040	-0.062	.939
	1.8	-2.5	4.9	1.9	2.6	1.1	-0.23	.	-1.1	-2.1	-10.8	
CAP	0.032	-41.1	2.15	4.81	-1.25	0.55	2.00	.	0.004	-0.013	-0.122	.887
	0.027	-0.545	0.629	1.77	-6.42	2.48	0.75	.	0.15	-0.58	-15.6	
MACH	-19.5	-432.	-5.24	26.5	-0.798	-0.129	3.03	.	-0.015	-0.019	-0.153	.914
	-6.6	-1.9	-0.53	3.8	-2.2	-0.52	0.71	.	-0.59	-0.76	-9.1	
CHEM	-3.1	-169.	-7.04	8.23	-0.796	-0.247	-2.34	.	-0.021	-0.021	-0.035	.903
	-1.3	-0.89	-0.85	1.4	-2.4	-1.0	-0.59	.	-0.84	-0.86	-2.4	

^aGNP is measured in thousands of dollars, CAPITAL in millions.

^b*t*-statistics appear beneath estimated coefficients.

Table 7b: Posterior Means of Coefficients of GNP and Net Export Equations for Rich Countries

	CAPITAL	LABOR1	LABOR2	LABOR3	LAND1	LAND2	LAND3	LAND4	COAL	MINERALS	OIL	R ²
GNP ^a	493.	30255.	-2138.	2422.	-0.497	6.82	98.9	-9.68	1.03	0.538	2.09	.998
	24.2	13.6	-5.8	3.4	-0.025	0.86	4.7	-1.1	4.2	2.2	11.0	
PETRO	-8.98	-589.	-204.	78.4	-0.454	-0.063	3.61	0.997	-0.025	-0.023	0.276	.972
	-5.1	-2.6	-6.1	1.2	-0.91	-0.26	1.3	1.2	-1.0	-0.93	11.1	
MAT	-1.51	-34.0	-176.	70.0	-0.467	-0.208	2.60	2.84	0.482	0.692	0.049	.950
	-0.83	-0.13	-5.2	1.1	-0.93	-0.84	0.90	2.5	4.4	4.5	1.6	
FOR	1.40	26.7	-75.9	76.7	-0.498	-0.200	-0.351	6.45	-0.017	-0.020	0.027	.639
	0.68	0.11	-2.1	1.0	-1.0	-0.81	-0.11	5.7	-0.68	-0.80	1.4	
TROP	-2.64	-283.	18.5	41.7	1.90	0.562	7.48	-0.934	-0.057	-0.017	0.027	.776
	-2.2	-1.7	0.89	0.96	1.0	1.1	3.4	-1.7	-2.4	-0.69	1.8	
ANL	1.15	-202.	-43.3	55.7	-0.501	0.660	8.71	-0.157	-0.022	-0.022	-0.002	.297
	0.43	-0.74	-0.95	0.56	-1.0	1.2	1.5	-0.11	-0.88	-0.89	-0.078	
CER	1.03	1358.	-243.	125.	1.94	1.29	22.2	1.93	0.014	-0.008	0.180	.956
	0.71	7.2	-9.7	2.4	1.0	2.5	8.3	2.7	0.56	-0.33	10.8	
LAB	-3.94	-483.	145.	67.2	-0.501	-0.262	-4.24	-2.20	-0.032	-0.025	-0.031	.629
	-1.52	-1.82	3.27	0.709	-1.00	-1.05	-1.12	-1.63	-1.29	-1.01	-1.48	
CAP	10.4	-1732.	197.	-113.	-0.490	-0.308	-11.6	-3.05	-0.049	-0.031	-0.113	.888
	4.6	-7.0	5.0	-1.3	-0.98	-1.2	-3.4	-2.7	-2.0	-1.3	-5.6	
MACH	30.6	-1960.	110.	-135.	-0.521	-0.320	-12.2	-8.27	-0.027	-0.033	-0.070	.823
	6.7	-3.2	2.0	-1.1	-1.0	-1.3	-2.7	-4.4	-1.1	-1.3	-2.9	
CHEM	5.1	464.	-77.1	-65.3	-0.487	-0.232	-6.50	-1.94	-0.010	-0.026	-0.035	.728
	2.6	1.7	-2.5	-1.0	-0.97	-0.94	-2.3	-2.3	-0.42	-1.1	-1.8	

^aGNP is measured in thousands of dollars, CAPITAL in millions.

^bt-statistics appear beneath estimated coefficients.

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NOTES

¹There is no mention of such assessments in two recent and comprehensive surveys of empirical research on trade (Leamer, 1992; Leamer and Levinsohn, 1995). In an earlier work, rightly regarded as paradigmatic for good econometric work on international trade, Leamer notes that a model with more than one cone “could be handled at an empirical level by estimating separate trade functions for each cluster of countries, but in the absence of knowledge of what those clusters may be, this presents formidable estimation problems, especially because many clusters may have too few countries for ordinary least-squares estimation” (1984: 156).

²I use a revised figure for the CAPITAL of Indonesia (\$24491.5 million), kindly supplied by Professor Harry P. Bowen.

³Angles between vectors are sensitive to the unit in which their components are expressed. CAPITAL, COAL, MINERALS, and OIL are expressed in dollars in Leamer’s data set, while three grades of labor and four kinds of land are measured in physical units. To express the factors in common units, I divide each factor by its cross-national mean. After thus standardizing the factors, I calculate the angle θ between the factor vectors x_i and x_j for countries i and j using a formula given by Theil (1971):

$$\theta = \arccos \left(\frac{x'_i x_j}{(x'_i x_i)^{1/2} (x'_j x_j)^{1/2}} \right).$$

⁴Other techniques for testing the one-cone hypothesis while allowing for heteroskedasticity include an asymptotic Chow bounds (ACB) test and a modified asymptotic Chow test, version two (MAC2), as described by Thursby (1992). Their results, which also reject the one-cone hypothesis, are reported in a preliminary version of this paper, which is available from the author.

⁵In Schwarz’s derivation of the criterion, the sample information dominates the prior when the prior is fixed and the sample size becomes large. In an alternative derivation (Klein and Brown, 1984), more relevant to our small sample, the sample dominates the prior when the sample size is fixed and the prior information is minimized.

⁶Leamer mentions two reasons why an estimate of the coefficient of CAPITAL might be higher than 170: “First,...the capital stock number is likely to be a serious underestimate.

Second, unmeasured resources that contribute to GNP cannot sensibly be assumed to be uncorrelated with capital” (1984: 145). Citing these reasons, he adopts 500 rather than 170 as a prior mean for the CAPITAL coefficient. However, the two points raised by Leamer seem more relevant to guessing the OLS estimates of coefficients than to specifying the distribution of the theoretical coefficients (marginal products). Thus we stick with 170 as a prior mean.

⁷Brazil and the Netherlands are used rather than the mediods (Dominican Republic and France) because they offer more complete data on wages. Theoretically, of course, wages should be the same for all countries within a single cone.

⁸Leamer (1984) sets the prior means for coefficients of subterranean resources at 1.0.

⁹Here we neglect an implication of Rybczynski’s theorem—namely, that an increase in a resource causes contraction of industries that are not intensive users of it.

¹⁰The estimates in Tables 7a and 7b are obtained by mixed estimation in RATS 4.0. The point estimates are the same as posterior means derived by a full Bayesian analysis with a natural conjugate prior distribution. However, the *t*-statistics reported here, like those in Leamer (1984), only approximate their full Bayesian counterparts.

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