Capital Abundance and Developing Country Production Patterns

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Abstract

We develop a model of two factors and two industries. Each industry contains a labor-intensive good and a capital-intensive good but industries differ in shares of the two goods. The model yields the usual Rybczynski prediction under factor price equalization, but it predicts the opposite in an equilibrium with unequal factor prices and a positive association between capital intensity and technology sophistication. Using a sample of 14 developing countries, 28 manufacturing industries and eleven years, we find evidence supporting the latter prediction. The output shares of labor (capital)-intensive industries are found to increase (decrease) with capital abundance after controlling for technology, skill and trade barrier.

Key words: Production patterns; Capital abundance; Factor price equalization; Multiple diversification cones; Developing countries

JEL classification: F1

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1 Introduction

The standard Heckscher-Ohlin (HO) model has been constantly challenged but has remained at the center of modern trade theory. The message from recent empirical work (e.g. Davis and Weinstein, 2001) is that the HO model surely does not fit the data but the role of resources remains important and cannot be denied. One factor identified by Davis and Weinstein (2001) that significantly helps explain global (factor) trade is production specialization due to unequal factor prices across countries, or the existence of multiple diversification cones. Studies by Schott (2001) and others provide additional evidence of multiple diversification cones. Accepting that resources still matter importantly and there is no factor price equalization (non-FPE), we face a question: Do resources matter differently in a non-FPE world?

In this paper we examine how resources affect production patterns of developing countries. To compare the resource-output relationship under non-FPE with that under FPE, we develop a simple model. In the model we distinguish between "HO goods" defined by capital intensity and "industries" that group goods of different capital intensities. Assuming two industries each containing two goods (one labor-intensive, one capital-intensive) and that the capital (labor)-intensive industry contains a larger output share of the capital (labor)-intensive good, we show that, under FPE, an increase in a country's capital abundance, by expanding the output of the capital-intensive HO good and contracting the output of the labor-intensive HO good, increases the output of the capital-intensive industry and decreases the output of the labor-intensive industry. This result, stated as Proposition 1, establishes the Rybczynski (1955) prediction between capital abundance and outputs of heterogeneous industries.

Our model yields a sharply different prediction under non-FPE. For a small open labor-abundant country in a non-FPE world, it produces only the labor-intensive goods of the two industries. An increase in the country's capital abundance expands the total output of labor-intensive goods. Without further characterization of the two industries we cannot determine the industry distribution of this output expansion. However, if we assume that the labor-abundant country faces a larger technology gap in a more capital-intensive industry, we can show that the labor-intensive good of the capital-intensive industry must be more labor-intensive than the labor-intensive good of the labor-intensive industry for both goods to be produced in the country. This leads to the prediction, stated as Proposition 2, that an increase in the developing country's capital abundance will *decrease* the output of its capital-intensive industry and *increase* the output of its labor-intensive industry, contrary to the prediction under FPE!

Guided by the theory, we investigate empirically the relationship between production patterns and capital abundance in a sample of 14 developing countries, 28 manufacturing industries, over the period 1982-1992. The choice of country and time period is dictated by data availability. Table 1 lists the 14 countries ranked in ascending order of capital abundance. In the sample, India is most labor-abundant and Singapore is most capital-abundant. Table 2 lists the 28 industries ranked in ascending order of capital intensity. In the sample, wearing apparel and footwear are the most labor-intensive industries, and petroleum refineries and industrial chemicals are the most capital-intensive industries. We measure production patterns by industry value-added shares in total manufacturing. For example, the value-added share of the iron and steel industry in India was 12% in 1982 and 8% in 1992. The changes in all 28 industries in value-added share reflect the evolution of a country's production patterns over the sample period.

We are interested in how production patterns respond to a change in capital abundance. To get an idea, we can take a look at how industry value-added shares changed in each country. All countries in our sample except Poland became more capital-abundant over the period 1982-1992. Figure 1 depicts the average annual growth rates of industry value-added share in Chile and Indonesia, with industries ranked in ascending order of capital intensity. The figure reveals that on average labor-intensive industries expanded and capital-intensive industries contracted. Such a pattern is found for seven of the 14 developing countries in our sample.

Moving beyond the simple correlation shown in Figure 1, we use regressions to isolate the effect of capital abundance by controlling for other factors that influence production patterns. Our empirical investigation uses the estimation approach of Harrigan and Zakrajšek (2000), which is developed from the GDP function method of Diewert (1974) and Kohli (1978). The Harrigan-Zakrajšek approach uses panel-data regressions to account for differences in technologies and commodity prices without measuring them. In their study of the Rybczynski effects in a sample of 21 industrialized countries and 7 relatively advanced developing countries (Argentina, Chile, Hong Kong, Korea, Mexico, Turkey, and Taiwan) with four factors (unskilled labor, skilled labor, capital, and land) and 10 sectors (grouped from 3-digit ISIC industries), they found that the estimated Rybczynski effects have the expected signs in a significant number of industries, particularly in large industries that are not natural-resource based.

Our finding contrasts sharply with that of Harrigan and Zakrajšek (2000). We find capital abundance to be statistically significant in determining production patterns in 18 of the 28 industries (Table 3). However, the signs are opposite to what the standard HO model predicts. In our full-sample panel-data regressions controlling for time and country fixed effects as well as industry skill level (proxied by industry average wage rate relative to the US), the value-added shares of all of the 12 relatively labor-intensive industries *increase* with country capital abundance, with six of them statistically significant, and the value-added shares of 12 of the 16 relatively capital-intensive industries *decrease* with country capital abundance, with six of the 12 statistically significant (Table 4).

A valid application of the Harrigan-Zakrajšek regression equation requires conditional factor price equalization for countries in the sample.[1] Performing a test of conditional FPE that estimates the correlation between industry capital intensity and country capital abundance in

[1] If factor prices are not equalized conditional on technology differences, countries would produce different sets of goods, and the estimated Rybczynski effect would switch signs with respect to different levels of capital abundance (Leamer, 1987). Estimating a single Rybczynski equation in this case is not valid.

a pooled regression with industry fixed effects,[2] we reject the hypothesis of conditional FPE for our full sample of 14 countries (Table 5). To search for a group of countries located in the same cone that allows a legitimate application of the Harrigan-Zakrajšek regression equation, we perform the conditional FPE test on different groups of countries in our sample, starting with a pair of most labor-abundant countries (India and Indonesia). Adding labor-abundant countries one by one, we find evidence of conditional FPE for the seven most labor-abundant countries (Table 5). With conditional FPE holding for this subsample, we estimate a single Rybczynski equation. The results show the same pattern as that of the full sample (Table 6). We find that the value-added shares of 11 of the 13 relatively labor-intensive industries *increase* with country capital abundance, with six of them statistically significant, and the value-added shares of 10 of the 15 relatively capital-intensive industries *decrease* with country capital abundance, with five of the 10 statistically significant. These results are contrary to the prediction of the standard HO model but are consistent with the prediction of our non-FPE model. It is worth noting that the kind of small open economy HO models with non-FPE were well discussed and analyzed in Findlay (1973, chapter 9), Jones (1974), and Deardorff (1979) and more recently, in Findlay and Jones (2001), and Deardorff (2001). The contribution of this paper is to develop such a model that links observed industries to unobserved HO goods, use the model to predict a distinctively difference response of industry production patterns to capital abundance, and provide empirical evidence supporting the prediction of the model.

The remainder of the paper is organized as follows. In section 2 we develop a model that allows a comparison of the output-endowment relationships under FPE and non-FPE. In section 3 we discuss the empirical approach and lay out the regression equation. In section 4 we describe the data. In section 5 we present the results. In section 6 we conclude.

[2]This test has been performed by Dollar, Wolff, and Baumol (1988) and Davis and Weinstein (2001). See Harrigan (2001, p. 20) for a discussion of this test.

2 Theory

In this section we compare two models in their predictions on the output-endowment relationship in a small open economy. One is the standard HO model with factor price equalization (FPE), the other is an HO model with no factor price equalization (non-FPE).

Consider first the standard HO model of two factors, capital (K) and labor (L), and two goods, capital-intensive X and labor-intensive Y. Suppose there are two industries, T (textiles) and E (electronics). Our data identifies industries but not X and Y. Each industry contains both labor-intensive and capital-intensive goods. Assume that industry T has a share α of good Y_1, which is labor-intensive, and a share $(1-\alpha)$ of good X_1, which is capital-intensive. Similarly, E has a share β of labor-intensive good Y_2 and a share $(1-\beta)$ of capital-intensive good X_2. For our illustration, assume that Y_1 and Y_2 have the same capital intensity, so do X_1 and X_2. Thus there are two "HO goods", $X = X_1 + X_2$ and $Y = Y_1 + Y_2$. Both α and β are endogenously determined and we assume "no factor intensity reversal" of industries ($\alpha > \beta$) in the relevant equilibria. With these assumptions, we remain in the 2x2 HO framework. What is new is that we distinguish HO goods (X and Y) from industries (T and E). The Rybczynski theorem states the relationship between (X, Y) and capital abundance $k \equiv K/L$. Proposition 1 below establishes the relationship between (E, T) and capital abundance k.

Proposition 1. In a FPE world, if capital abundance of a small open economy increases, the capital-intensive industry E expands and the labor-intensive industry T contracts.

Consider next a non-FPE world. With unequal factor prices, trade leads to specialization. A labor-abundant small open economy produces only the labor-intensive good Y. In our model good Y can be Y_1 (labor-intensive textiles) or Y_2 (labor-intensive electronics). Without further characterization of the two industries, the output of Y_1 and Y_2 cannot be determined. To break up this indeterminacy, we introduce exogenous technology differences. Assume that good Y_1

and good Y_2 are identically priced at $p^1 = p^2 = 1$ in the world market because they have identical unit labor and capital requirements based on world production technology. Assume, however, that there is a gap between the labor-abundant country's technology and the world's technology, and the gap is larger the higher the capital intensity of an industry.[3] Write the unit cost function of good Y_1 as $c^1 = c(w, r)$ and that of good Y_2 as $c^2 = \theta d(w, r)$, where w and r are the equilibrium wage and rental rates in the country, and $\theta > 1$ captures the relatively large technology gap (measured by total factor productivity) of the country in sector E. For the country to produce both Y_1 and Y_2, the zero-profit conditions require $c(w, r) = \theta d(w, r) = 1$. It can be verified that the capital intensity of good Y_2 must be lower than that of good Y_1 to offset its technology disadvantage associated the larger technology gap. Since good Y_1 is more capital-intensive than good Y_2, we can apply the Rybczynski theorem to establish:

Proposition 2. In a non-FPE world, a small open labor-abundant country specializes in labor-intensive goods. If there is a technology gap between the country and the world that is larger the higher the capital intensity of an industry, and if the country produces in all industries, then as the country becomes more capital-abundant, the labor-intensive industry T expands and the capital-intensive industry E contracts.

Propositions 1 and 2 show the sharply different predictions of the two models on output responses to endowment changes. One wonders to what extent these results can be generalized. To get an idea, consider the case of two factors (capital and labor), n (> 2) goods, and j (> 2) industries. In the FPE model, with more goods than factors, there does not exist a unique relationship between output and capital abundance. In the non-FPE model without technology differences, a small open labor-abundant country will specialize in one labor-intensive good. In the presence of the technology gap described in Proposition 2, the country will specialize

[3] We assume this pattern of technology gap based on the belief that more capital-intensive industries tend to be more technologically sophisticated.

in a set of labor-intensive goods that belong to different industries, with capital intensity of the good in the country inversely related to the capital intensity of the industry in the world. As in the FPE model, with more goods (industries) than factors, there does not exist a unique relationship between output and capital abundance. This example indicates that a generalization of Propositions 1 and 2 to higher dimensions is difficult.[4] Nevertheless, as now widely recognized, the determinacy of output patterns is not a question of counting the numbers of goods and factors, but a question that requires empirical estimation to settle (Harrigan, 2001, p. 15).[5] With this understanding, we set the issue aside and turn to empirical estimation to see if the data reveals any systematic pattern.

3 Empirical Approach

In this section we describe a panel-data approach for estimating the effects of capital abundance on output. This approach was developed by Harrigan and Zakrajšek (2000).

Consider a world of many countries, n factors, and n final goods. Factors are completely mobile within a country but are completely immobile between countries. Consider a small open economy that produces all n goods. World commodity prices are given by an nx1 vector $\mathbf{P}^*$, and domestic prices are given by an nx1 vector $\mathbf{P}$; these two price vectors may differ due to trade barriers. Let $\mathbf{W}$ be an nx1 vector of domestic factor prices, and $\mathbf{C}(\mathbf{W})$ be an nx1 vector of unit cost functions. Production technologies are assumed to be neoclassical so the unit cost functions are increasing, concave, and homogeneous of degree one in factor prices.

The unit cost functions imply an nxn production technique matrix $\mathbf{A}$. The element of $\mathbf{A}$ is a_{ij} for good i and factor j, which is obtained from partial differentiation of good i's unit cost

[4] There can be a weak generalization however in the "even" case of equal number of factors and goods. Ethier (1984) states this generalization as "endowment changes tend on average to increase the most those goods making relatively intensive use of those factors which have increased the most in supply" (p. 168).

[5] Bernstein and Weinstein (2002) is a pioneering paper to address empirically the question of output indeterminancy in the HO model.

function with respect to factor j's price. Let $\mathbf{V}$ be an nx1 vector of factor supplies, and $\mathbf{Y}$ be an nx1 vector of good supplies. Perfect competition in factor markets leads to the following full-employment conditions:

$$\mathbf{V} = \mathbf{AY}. \tag{1}$$

With perfect competition in good markets, we also have the following zero-profit conditions:

$$\mathbf{P} = \mathbf{C}(\mathbf{W}). \tag{2}$$

Equations (1) and (2) characterize the general-equilibrium determination of $\mathbf{W}$ and $\mathbf{Y}$ at given $\mathbf{P}$ and $\mathbf{V}$. Assume that Nikaido's (1972) condition is satisfied, we obtain from (2) a unique solution of factor prices, $\mathbf{W} = \mathbf{C^{-1}}(\mathbf{P})$. Provided that $\mathbf{A}$ is nonsingular at the equilibrium factor prices, we obtain from (1) a unique solution of commodity supplies, $\mathbf{Y} = \mathbf{A^{-1}}(\mathbf{W})\mathbf{V}$.

We are interested in the effects of factor supplies ($\mathbf{V}$) on commodity supplies ($\mathbf{Y}$), known as "Rybczynski effects". In this nxn model, using subscript 0 to denote the initial equilibrium and 1 the equilibrium after changes in factor supply, we have (Ethier, 1984, p. 167):

$$(\mathbf{V_1} - \mathbf{V_0})\mathbf{A}(\mathbf{W})(\mathbf{Y_1} - \mathbf{Y_0}) > \mathbf{0}. \tag{3}$$

This result says that factor supply changes will raise, on average, the output of goods relatively intensive in those factors whose supply has increased the most and will reduce, on average, the output of goods which make relatively little use of those factors whose supply has increased the most. Notice that $\mathbf{W}$ has to remain the same in the two equilibria for this result to hold.

To estimate the Rybczynski effects, we use the GDP function method developed by Diewert (1974) and Kohli (1978). With perfect competition, market-determined commodity outputs equal the ones chosen by a social planner who maximizes gross domestic product. Let the GDP function be $G = G(p_1, p_2, ...p_n, V_1, V_2, ...V_m)$. If the GDP function is first-order differentiable, its partial derivatives on commodity prices show the Rybczynski effects, and its partial derivatives on factor supplies show the Stolper-Samuelson effects. Applying a second-order Taylor approximation in logarithms to the GDP function yields a translog GDP function:

$$\ln G = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \sum_{k=1}^{m} \beta_k \ln V_k + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j + \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m} \delta_{kl} \ln V_k \ln V_l + \sum_{i=1}^{n}\sum_{k=1}^{m} \phi_{ik} \ln p_i \ln V_k. \tag{4}$$

Differentiating (4) with respect to $\ln p_i$ yields an output share equation:

$$s_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \sum_{k=1}^{m} \phi_{ik} \ln V_k, \tag{5}$$

where $s_i \equiv d\ln G/d\ln p_i = p_i Y_i/G_i$ is the value-added share of good i in GDP. Note that homogeneity properties imply $\sum_{i=1}^{n} \alpha_i = 1$, $\sum_{j=1}^{n} \gamma_{ij} = 0$, and $\sum_{k=1}^{m} \phi_{ik} = 0$.

3.1 Modeling Technology and Price Differences

So far we have been describing a single country with time-invariant technologies and commodity prices. To isolate the effects of factor endowments on production patterns, we need to consider differences in technologies and good prices across country and over time. We start by following Harrigan (1987) in using an nx1 vector $\mathbf{\Theta}$ to capture sector-specific Hicks-neutral technology differences across countries (assumed constant over time). In this case the GDP function is written as $G = G(\theta_1 p_1, \theta_2 p_2, ...\theta_n p_n, V_1, V_2, ...V_m)$, where θ_i is an element of $\mathbf{\Theta}$. Using c as a country subscript and t a time subscript we write the output share equation as

$$s_{ict} = \alpha_i + b_{ic} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jct} + \sum_{k=1}^{m} \phi_{ik} \ln V_{kct}, \tag{6}$$

where $b_{ic} \equiv \sum_{j=1}^{n} \gamma_{ij} \ln \theta_{jct}$ is a country-specific constant that captures industry-specific Hicks-neutral technology differences across countries.

There are still non-neutral technology differences across countries and technology differences across time. There are also differences in domestic good prices across countries and over time due to trade barriers. To capture these differences, we follow Harrigan and Zakrajšek (2000) to use an approximation for the price summation term in equation (6):

$$\sum_{j=1}^{n} \gamma_{ij} \ln p_{jct} = d_{ic} + d_{it} + \eta_{ict}. \tag{7}$$

Equation (7) assumes that at any time t, commodity price p_{ict} differs across countries by a country-specific parameter d_{ic}; this can be a result of a non-neutral technology difference or a trade-barrier difference. It also allows commodity price p_{ict} to differ across time by a time-specific (but common across countries) parameter d_{it}; this captures the time variation of global technologies and trade barriers. There remain country-specific time-variant price differences; we model them by an error term η_{ict}. Substituting (7) into (6) yields

$$s_{ict} = \alpha_i + \delta_{ic} + d_{it} + \sum_{k=1}^{m} \phi_{ik} \ln V_{kct} + \eta_{ict}, \tag{8}$$

where $\delta_{ic} = b_{ic} + d_{ic}$ captures the combined effect of cross-country time-invariant (neutral and non-neutral) technology differences and price differences.

3.2 Estimation Equation

For our purpose, we need to derive an estimation equation with two factors from the n-factor model. To do so, we assume that the n factors belong to two categories, labor and capital. Let K be the aggregation of various capital factors, and L be the aggregation of various labor factors. Both capital and labor are heterogeneous. We consider sophistication of capital as part of "technologies" and assume heterogeneity of labor in industry-specific skill. Industry i in country c employs L_{hic} skilled workers who are immobile between industries and L_{lic} unskilled workers who are mobile between industries. We will make output share of industry i dependent on industry skill level h_{ic} and treat $L_c = \sum_i (L_{hic} + L_{lic})$ as country c's labor endowment. Taking these considerations into account, we obtain the following output share equation:

$$s_{ict} = \alpha_i + \delta_{ic} + d_{it} + \phi_i \ln(K/L)_{ct} + \rho_i \ln h_{ict} + \varepsilon_{ict}. \tag{9}$$

Equation (9) is the regression equation for our estimation. With data pooled over countries and time, the output share of industry i depends on country-specific effects δ_{ic}, time-specific effects d_{it}, capital abundance $(K/L)_{ct}$, industry skill level h_{ict}, and all other remaining factors ε_{ict}.

4 Data

The data for our study are mainly from UNIDO Industrial Statistics Database (3-Digit ISIC Code, 1963-1999) and the World Bank Trade and Production Database (3-Digit ISIC Code, 1976-1999).[6] The production data in the World Bank database are the same as those in the UNIDO database, but the World Bank database also contains trade data in 3-Digit ISIC Code. The data in these two databases are in current U.S. dollars. Penn World Tables provide price parities for value added and investment. We use them to convert all current values to internationally comparable values in 1985 international dollar.

All capital stocks are computed using the perpetual inventory method, with 1975 as the initial year and 10% as the discount rate. Industry capital stocks are computed from UNIDO industry-level investment data. Country capital stocks are computed from investment data in the Penn World Tables. Our sample contains 14 developing countries (Table 1). These are the only 14 developing countries that have a relatively complete industry-level investment series from which we construct industry capital stocks. The sample period is 1982-1992.[7]

For each industry we calculate its value-added share in total manufacturing. We also calculate the wage rate relative to the U.S. as a proxy for the skill level of an industry, and exports plus imports in manufacturing value added as a measure of industry trade openness. At the 3-digit ISIC level every country exports and imports in every industry.

[6]See Nicita and Olarreaga (2001) for the document of the World Bank database.

[7]We choose 1982 as the beginning year because the investment series starts in 1975 for most of the countries and we need several years of investment accumulation for estimated capital stocks to be relatively insensitive to initial-year investment. The choice of 1992 is because it is the ending year of the Penn World Tables.

5 Empirical Results

5.1 Estimating Rybczynski Effects: Full Sample

In Table 3 we report results from estimating equation (9) using both fixed-effects and random-effects methods. The results are quite similar between the two methods. The Hausman test supports the hypothesis of no correlation between the independent variables and the country-specific effects in almost all cases, so the random-effects estimator is valid. As Harrigan and Zakrajšek (2000) point out, the random-effects estimator is useful because it captures some of the cross-country variation in the data.

Table 3 shows our main finding: capital abundance (K/L) tends to have a positive effect on the value-added shares of relatively labor-intensive manufactured industries, and a negative effect on the value-added shares of relatively capital-intensive manufactured industries. In 14 of the 16 most labor-intensive industries, the estimated effects of (K/L) are positive, and 11 of them are statistically significant (random-effects estimation). In nine of the 12 most capital-intensive industries, the estimated effects of (K/L) are negative, and four of them are negative and statistically significant. This finding is contrary to the prediction of the standard HO model but consistent with the prediction of our non-FPE model (Proposition 2).

In Table 3 we do not control for the skill level of the labor force. If an industry is labor-intensive due to intensive use of skilled labor, then an increase in a country's capital abundance, often accompanied by an increase in its skill abundance, can lead to a positive correlation between output shares and (K/L). Harrigan and Zakrajšek (2000) distinguish skilled labor and unskilled labor. As we argue in section 2, if skilled labor is industry-specific, then we may control for its effect using an industry skill measure. The industry average wage rate relative to the U.S. provides a proxy for industry skill level. Table 4 reports results from regressions that include this skill variable. We find the same pattern as that of Table 3. Only two industries see noticeable changes: the estimated effect of (K/L) on textiles (321) turns from positive and statistically significant without controlling for skill to negative and statistically insignificant with skill controlled for, and the estimated effect of (K/L) on fabricated metal products (381) turns from positive and statistically significant to positive and statistically insignificant. The estimated effects of the skill variable are statistically significant in 14 of the 28 industries, with nine of the 14 showing a positive estimated coefficient, suggesting that most manufacturing industries would see output share to increase with skill.

5.2 Identifying a Subsample with Conditional FPE

Estimating a single Rybczynski equation (9) is valid only if factor prices are conditionally equalized in the sample. Otherwise countries would produce different sets of goods and the estimated Rybczynski effect would switch signs with respect to different levels of capital abundance.

The literature offers a simple test of conditional FPE. Under conditional FPE, countries produce the same set of goods. A change in factor supplies will be fully absorbed by output-share adjustments, leaving factor prices unchanged. As a result, production techniques will be insensitive to factor-supply changes. This suggests, in the two-factor case, the following regression equation for testing the conditional FPE hypothesis:

$$\left(\frac{K}{L}\right)_{ict} = \alpha_{it} + \beta_t \left(\frac{K}{L}\right)_{ct} + \nu_{ict}. \tag{10}$$

In regression equation (10), the dependent variable is industry capital intensity, and the independent variable is country capital abundance. Pooling data across country and industry for any time t, we have industry capital intensity $(K/L)_{ict}$ dependent on industry-specific fixed effects α_{it}.[8] Under the null hypothesis of conditional FPE, we have $\beta_t = 0$. The error term ν_{ict} is assumed to be zero-mean random technology shocks. If there is no conditional FPE, then $\beta_t \neq 0$. In particular, non-FPE models (e.g. Dornbusch, Fischer, and Samuelson, 1980) predict

[8] The regression does not include country-specific fixed effects because neutral technology differences across countries do not affect capital intensity.

that $\beta_t > 0$: the goods produced by a labor-abundant country are more labor-intensive than the goods produced by a capital-abundant country.

Table 5 reports results from estimating (10). The first row of Table 5 reports the results for the full sample of 14 countries. We find that the estimated β is positive and statistically significant at the 1 percent level, clearly rejecting conditional FPE in the full sample.[9]

One reason for factor prices not equalized is that countries have very different capital abundance. To see if conditional FPE holds for a subsample of countries which have similar capital abundance, we apply regression (10) first to a pair of most labor-abundant countries, India and Indonesia. The estimated β is positive, but the statistical significance level is only 10 percent. If we add to the sample the next labor-abundant country, Egypt, then the estimated β becomes statistically indifferent from zero. Continuing this experiment, we find that the estimated β is indifferent from zero for the subsample of the seven most labor-abundant countries in 1992. This is true in 1982 as well. These results suggest that conditional FPE holds among the seven most labor-abundant countries in our sample. Their capital abundance is similar enough for them to produce similar goods. Table 5 also shows some evidence that the three most capital-abundant countries (Korea, Hong Kong, and Singapore) form a single cone of diversification.

5.3 Estimating Rybczynski Effects: Subsample

Given conditional FPE in the subsample of the seven most labor-abundant countries, we can run a single Rybczynski regression on this subsample. Table 6 reports the results.[10] We find the

[9]We also use the decomposition method of Hanson and Slaughter (2002). The method is to decompose the changes in factor supply into output-mix changes, generalized changes in production techniques, and idiosyncratic changes in production techniques. In their examination of U.S. states, Hanson and Slaughter find that state-specific changes in production techniques play a relatively small role and interpret it as evidence of conditional FPE among U.S. states. Our results show that country-specific changes in production techniques play a relatively large role (40% for labor and 29% for capital, averaged over the 14 countries for the period 1982-1992), which supports our rejection of conditional FPE for countries in our sample.

[10]The industries in Table 6 are ranked in ascending order of average capital intensity of the subsample. The second and third columns compare the industry capital intensities between the full sample and the subsample. The average capital intensity of the 7 most labor-abundant country is significantly lower than that of the full sample, but the ranking is largely the same.

same pattern as in the full sample: labor-intensive manufacturing industries tend to expand and capital-intensive manufacturing industries tend to shrink as capital abundance increases. The value-added shares of 11 of the 13 relatively labor-intensive industries *increase* with country capital abundance, with six of them statistically significant, and the value-added shares of 10 of the 15 relatively capital-intensive industries *decrease* with country capital abundance, with five of the 10 statistically significant.

In our output share regressions we use time dummies to control for unobserved time-specific factors common to all countries, and country dummies to control for unobserved country-specific factors common across time. There remain country-specific time-variant unobserved factors that may affect the identification of the role of capital abundance. One such factor is trade barrier. For developing countries a lower trade barrier generally means more exports of labor-intensive goods and less imports of capital-intensive goods. If trade openness is positively correlated with capital abundance, then as a country becomes more abundant in capital it exports more labor-intensive goods and imports less capital-intensive goods, thus producing more labor-intensive goods and less capital-intensive goods. In fact, trade openness is found to have increased more in labor-intensive industries than in capital-intensive industries in seven of the 14 sample countries. Figure 2 depicts changes in industry trade openness in Chile and Indonesia, with the horizontal axis showing industries ranked in ascending order of capital intensity.

To control for the effect of industry-specific trade barrier that differs across country and over time, we introduce an additional independent variable T_{ict} defined as industry trade openness. In Table 7 we use industry exports plus imports in manufacturing value-added as a measure of industry trade openness. We find this variable to have a positive and statistically significant effect on value-added share of 11 industries, and a negative and statistically significant effect on one industry (371, iron and steel). We find, however, that adding this trade openness variable, while reducing the point estimates of the effects of capital abundance, does not change the signs of the effects. Capital abundance still has a positive and statistically significant effect on five labor-intensive industries, and a negative and statistically significant effect on six capital-intensive industries. The pattern remains to be the one contrary to the prediction of the standard HO model but consistent with the prediction of our non-FPE model.[11]

6 Conclusion

Recent empirical studies confirm the significance of factor abundance in understanding global production and trade but find technology and "multiple cones" equally significant, if not more. While the theoretical literature has long recognized it, it lacks a simple model that melts all these three elements and serves as a compelling alternative to the standard HO model. Such a model is especially needed for analyzing open developing economies, which face technology gaps and produce a mix of goods different from those produced by developed countries.

This paper is a small step toward this gigantic goal. We develop a model that distinguishes goods from industries. Goods are homogeneous but industries are not. With certain assumptions the model can be made equivalent to the 2x2 HO model, and has the implication that under FPE, an increase in the supply of a factor increases the output of the industry that uses intensively the factor and decreases the output of the other industry (at constant goods prices). By distinguishing between goods and industries, the model implies that a small open economy, under non-FPE, will produce only the goods with factor intensity equal to its factor abundance, and yet have positive production in all industries. This fills a gap between the prediction of the small open economy HO model that a country, under non-FPE, produces only one good

[11] We check the robustness of our results using data on aggregate capital stocks from Penn World Tables 5.6, which are available for nine of the 14 countries. Following Harrigan and Zakrajšek (2000) we aggregate producer durables and non-residential construction. The correlation between this capital stock measure and the measure constructed from investment series is 0.61. When this capital stock measure is used, only four estimated coefficients on $\log(K/L)$ are statistically significant. The pattern remains in that the estimated coefficients are positive for the two relatively labor-intensive industries (381 and 383) and negative for the two relatively capital-intensive industries (352 and 362).

(no more than two to be precise), and the observation that no country produces in a single industry (no matter how disaggregate the data is). Moreover, introducing a technology gap between the developing country and the world and assuming a positive correlation between the size of the gap and the capital intensity of the industry, the model yields a surprising prediction on the response of industry output to factor abundance. The model predicts, under non-FPE and the assumed pattern of technology gap, that an increase in the capital abundance of a small open labor-abundant country will *expand* its labor-intensive industry and *contract* its capital-intensive industry, contrary to the prediction of the standard HO model.

This surprising prediction finds empirical support from our investigation of a sample of 14 developing countries and 28 manufacturing industries over the period 1982-1992. Using a panel-data approach to control for unobserved country-specific and time-specific changes in technology, resources other than capital and labor, trade barriers, and others, as well as the observed changes in industry skill level and trade openness (that are neither country-specific nor time-specific), we find a pattern that is consistent with the prediction of our non-FPE model. The shares of labor-intensive industries tend to increase and the shares of capital-intensive industries tend to decrease, as country capital abundance increases.

Admittedly there are both theoretical and empirical unresolved issues regarding the validity of our finding. For example, our theoretical predictions derived from a two-dimension model seem difficult to generalize to higher dimensions. Large measurement errors exist in our data, particularly in capital stocks. The panel-data approach and our measure of industry trade openness may not capture the entire effect from trade barriers. And there are factors such as foreign direct investment that may be important but are not controlled for. All said, the unusual regularity found in the data is remarkable to this author and the results are worth reporting and can serve as a motivation for future theoretical modeling and empirical investigation.

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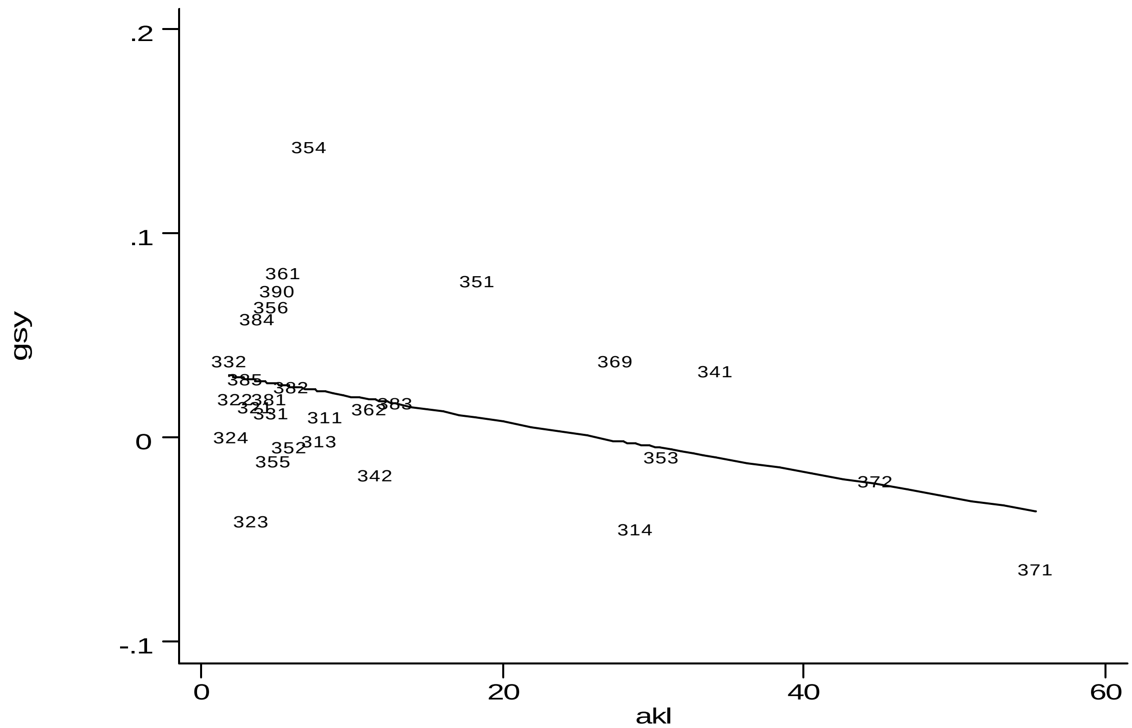

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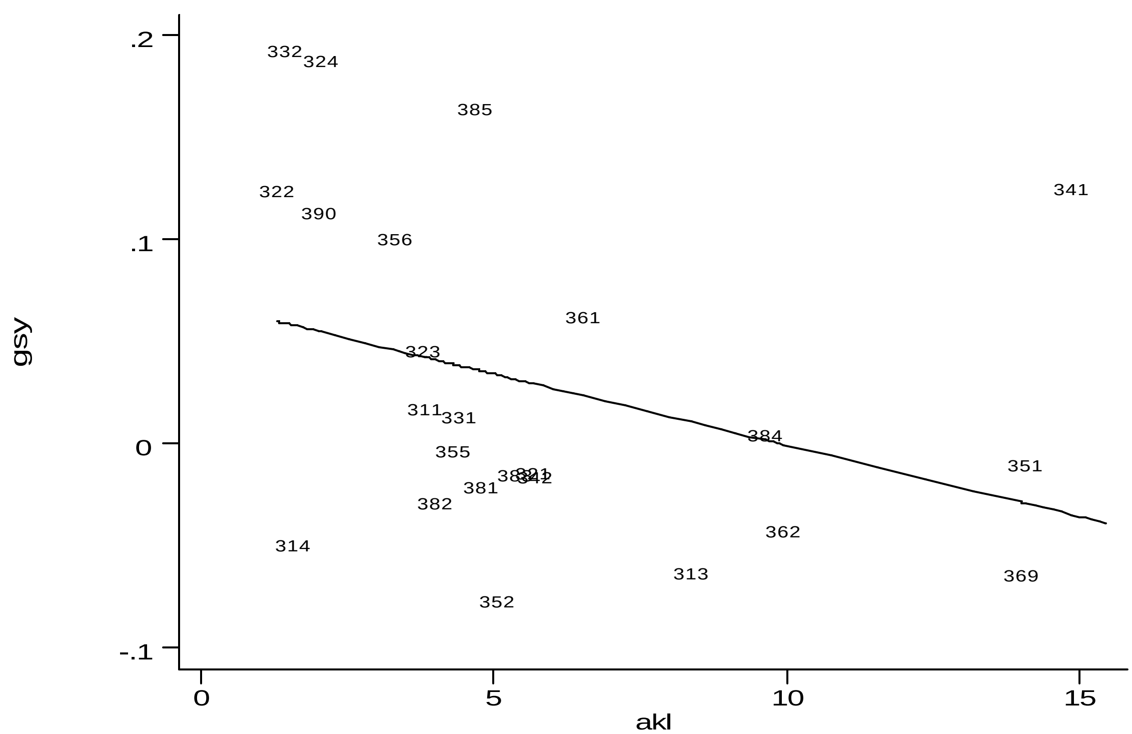
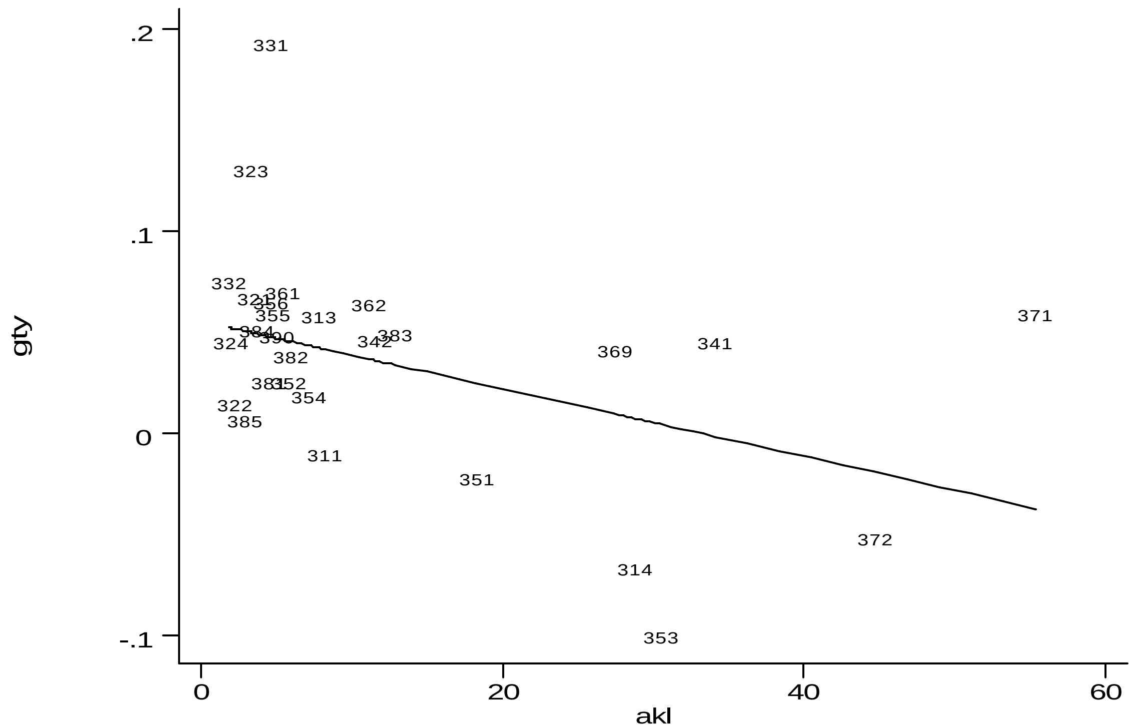


Indonesia

Figure 1. Average Annual Growth in Industry Value-Added Share (gsy)
with Industries Ranked in Order of Average Capital Intensity (akl), 1982-1992



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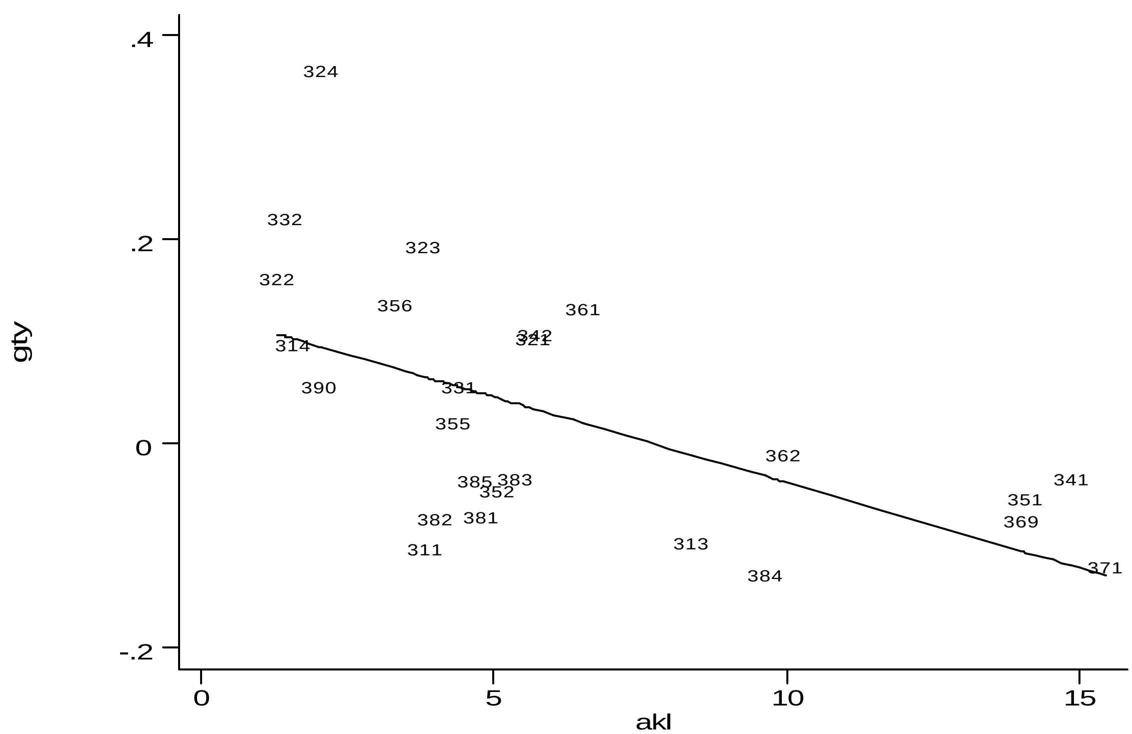

Indonesia

Figure 2. Average Annual Growth in Industry Trade Openness (gty)
with Industries Ranked in Order of Average Capital Intensity (akl), 1982-1992

Table 1. Countries in the Sample

Capital Abundance Rank (Low to High)	Country	Capital Abundance (K/L)		
		1982-1992 average	1982	1992
1	India	0.204	0.147	0.295
2	Indonesia	0.410	0.180	0.770
3	Egypt	0.429	0.342	0.404
4	Philippines	0.638	0.538	0.701
5	Colombia	0.792	0.643	0.817
6	Chile	0.812	0.604	1.233
7	Turkey	0.840	0.652	0.937
8	Malaysia	1.347	0.790	2.269
9	Hungary	1.714	1.303	2.123
10	Ecuador	1.801	1.821	1.899
11	Poland	1.879	2.096	2.093
12	Korea	2.183	1.270	3.438
13	Hong Kong	2.387	1.452	3.526
14	Singapore	6.494	4.312	7.694

Table 2. Industries in the Sample

L_i/K_i Rank	ISIC code	Industry	Value-added share	Capital Intensity		
				82-92 average	1982	1992
1	322	Wearing apparel except footwear	0.039	2.454	1.810	3.493
2	324	Footwear except rubber or plastic	0.007	4.126	3.141	6.281
3	332	Furniture except metal	0.008	4.980	3.731	10.809
4	390	Other manufactured products	0.011	6.591	6.090	8.441
5	323	Leather products	0.004	6.969	6.878	9.611
6	385	Professional and scientific equipment	0.012	8.658	6.661	12.144
7	381	Fabricated metal products	0.042	9.173	6.758	11.869
8	382	Machinery except electric	0.052	9.297	7.932	12.320
9	331	Wood products except furniture	0.023	9.369	8.506	10.965
10	342	Printing and publishing	0.025	10.167	8.061	13.194
11	356	Plastic products	0.023	10.795	8.316	14.667
12	361	Pottery china earthenware	0.005	10.983	10.601	11.676
13	321	Textiles	0.087	11.317	8.683	15.098
14	311	Food products	0.119	11.934	9.669	14.528
15	383	Machinery electric	0.093	12.113	9.047	18.710
16	384	Transport equipment	0.054	13.051	9.505	16.842
17	355	Rubber products	0.019	13.327	9.138	20.865
18	352	Other chemicals	0.054	14.185	10.374	20.355
19	313	Beverages	0.046	18.223	13.258	27.792
20	362	Glass and products	0.009	18.708	13.889	27.433
21	314	Tobacco	0.036	19.033	12.887	25.475
22	341	Paper and products	0.025	21.256	15.500	33.222
23	369	Other non-metallic mineral products	0.037	26.010	19.690	31.864
24	372	Non-ferrous metals	0.028	29.967	21.319	41.192
25	354	Misc. petroleum/coal products	0.007	30.424	20.203	55.979
26	371	Iron and steel	0.043	37.481	32.740	46.689
27	351	Industrial chemicals	0.046	38.869	30.175	55.833
28	353	Petroleum refineries	0.068	98.680	58.511	171.147

Table 3. Panel Regressions, Industry Value-Added Share, 14 Countries, 1982-1992

L_i/K_i rank	ISIC code	Random-Effects Estimation			Fixed-Effects Estimation		n	Hausman Test (Prob. rejecting H_0)
		Effect of ln(*K*/*L*)	Between R^2	Within R^2	Effect of ln(*K*/*L*)	Within R^2		
1	322	–0.003 (0.005)	0.108	0.027	–0.005 (0.005)	0.029	154	0.002
2	324	0.003 (0.001)***	0.000	0.167	0.006 (0.002)***	0.186	154	0.408
3	332	0.006 (0.001)***	0.379	0.244	0.008 (0.001)***	0.248	154	0.099
4	390	0.005 (0.002)***	0.301	0.165	0.005 (0.002)**	0.166	154	0.000
5	323	0.0014 (0.0005)***	0.018	0.132	0.002 (0.0007)***	0.136	154	0.003
6	385	0.004 (0.002)**	0.230	0.102	0.002 (0.002)	0.103	154	0.000
7	381	0.009 (0.002)***	0.507	0.117	0.007 (0.003)*	0.119	154	0.000
8	382	0.023 (0.009)***	0.236	0.107	0.022 (0.014)	0.107	154	0.000
9	331	0.005 (0.004)	0.073	0.102	0.008 (0.004)*	0.106	154	0.008
10	342	0.005 (0.002)**	0.340	0.051	0.002 (0.003)	0.055	154	0.001
11	356	0.006 (0.002)**	0.206	0.081	0.005 (0.0024)	0.081	154	0.000
12	361	0.001 (0.001)	0.002	0.105	0.002 (0.001)	0.105	142	0.000
13	321	0.004 (0.007)	0.228	0.342	0.015 (0.008)*	0.351	154	0.244
14	311	–0.022 (0.012)*	0.179	0.027	–0.016 (0.017)	0.028	152	0.000
15	383	0.043 (0.012)***	0.450	0.097	0.032 (0.015)**	0.099	154	0.000
16	384	0.011 (0.005)**	0.022	0.085	0.014 (0.006)**	0.086	154	0.000
17	355	–0.003 (0.002)	0.064	0.170	–0.0024 (0.003)	0.170	154	0.000
18	352	–0.013 (0.004)***	0.218	0.108	–0.014 (0.005)**	0.108	154	0.000
19	313	0.137 (0.006)**	0.001	0.177	0.016 (0.007)**	0.177	154	0.000
20	362	–0.0003 (0.0009)	0.000	0.113	–0.0006 (0.0011)	0.114	143	0.000
21	314	–0.019 (0.006)***	0.231	0.158	–0.020 (0.008)**	0.158	154	0.000
22	341	0.009 (0.002)***	0.024	0.285	0.012 (0.002)***	0.293	154	0.490
23	369	–0.004 (0.003)	0.115	0.117	–0.002 (0.004)	0.118	154	0.000
24	372	–0.001 (0.008)	0.054	0.135	0.002 (0.009)	0.136	146	0.000

25	354	0.0004 (0.0019)	0.070	0.169	0.006 (0.0034)**	0.197	116	0.051
26	371	–0.019 (0.005)***	0.418	0.189	–0.022 (0.008)***	0.189	143	0.000
27	351	–0.005 (0.005)	0.152	0.134	.0010 (0.007)	0.138	154	0.000
28	353	–0.036 (0.019)**	0.004	0.339	–0.169 (0.040)***	0.304	121	0.773

Notes: The dependent variable is industry value-added share. The fixed-effects estimation uses country-specific and time-specific dummies as independent variables. The random-effects estimation uses time-specific dummies as independent variables and a random country-specific error component. Asterisks indicate statistical significance level, with *** for less than 1 percent, ** for less than 5 percent, and * for less than 10 percent. The Hausman specification test is performed to test the null hypothesis H_0 that there is no systematic difference between estimated coefficients from the fixed-effects estimator and those from the random-effects estimator, provided that the model is correctly specified and there is no correlation between the independent variables and the country-specific effects.

Table 4. Panel Regressions, Industry Value-Added Share, 14 Countries, 1982-1992

L_i/K_i rank	ISIC code	Random-Effects Estimation		Between R^2	Within R^2	n
		Effect of ln(*K/L*)	Effect of ln(w_c/w_{US})			
1	322	0.000 (0.006)	–0.003 (0.003)	0.323	0.037	154
2	324	0.005 (0.001)***	–0.002 (0.001)***	0.007	0.226	154
3	332	0.005 (0.001)***	0.0004 (0.001)	0.349	0.255	154
4	390	0.007 (0.002)***	–0.003 (0.001)***	0.256	0.228	154
5	323	0.001 (0.0006)**	0.0004 (0.0003)	0.018	0.139	154
6	385	0.004 (0.002)**	0.000 (0.001)	0.230	0.102	154
7	381	0.006 (0.003)**	0.005 (0.002)**	0.525	0.147	154
8	382	0.016 (0.010)	0.012 (0.007)*	0.165	0.132	154
9	331	0.005 (0.004)	–0.001 (0.002)	0.057	0.103	154
10	342	0.0002 (0.002)	0.010 (0.002)***	0.508	0.226	154
11	356	0.005 (0.003)	0.001 (0.002)	0.239	0.082	154
12	361	0.001 (0.001)	0.001 (0.001)	0.005	0.121	142
13	321	–0.001 (0.008)	0.008 (0.005)	0.000	0.350	154
14	311	–0.030 (0.013)**	0.014 (0.008)*	0.200	0.049	152
15	383	0.046 (0.012)***	–0.009 (0.008)	0.446	0.105	154
16	384	0.011 (0.006)**	–0.000 (0.004)	0.022	0.086	154
17	355	–0.003 (0.002)	0.001 (0.001)	0.042	0.174	154
18	352	–0.018 (0.004)***	0.014 (0.003)***	0.234	0.246	154
19	313	0.010 (0.006)*	0.010 (0.003)***	0.006	0.238	154
20	362	–0.002 (0.001)*	0.002 (0.001)***	0.010	0.244	143
21	314	–0.029 (0.007)***	0.012 (0.004)***	0.140	0.231	154
22	341	0.011 (0.002)***	–0.005 (0.001)***	0.104	0.386	154
23	369	–0.008 (0.003)***	0.009 (0.002)***	0.042	0.241	153
24	372	–0.009 (0.008)	0.008 (0.004)**	0.295	0.153	146
25	354	–0.002 (0.002)	0.002 (0.001)	0.498	0.145	116

26	371	−0.018 (0.006)***	−0.002 (0.004)	0.432	0.189	143
27	351	−0.004 (0.005)	−0.002 (0.003)	0.143	0.136	154
28	353	−0.030 (0.020)	−0.049 (0.014)***	0.001	0.347	121

Table 5. Pooled Regressions, OLS with Robust Standard Errors

Countries in regression Country code: (*K/L*) rank	1992		1982	
	Estimated ***b***	Adjusted R^2	Estimated ***b***	Adjusted R^2
All countries	5.035 (0.839)***	0.396	3.039 (0.522)***	0.437
1, 2	4.359 (2.520)*	0.910	12.641 (33.572)	0.594
1, 2, 3	4.319 (4.001)	0.479	72.279 (13.038)***	0.549
1, 2, 3, 4	–0.675 (6.037)	0.510	6.689 (5.532)	0.231
1, 2, 3, 4, 5	–2.549 (5.242)	0.521	1.344 (3.801)	0.377
1, 2, 3, 4, 5, 6	2.042 (4.541)	0.470	3.024 (3.967)	0.283
1, 2, 3, 4, 5, 6, 7 (K/L < 1)	2.392 (4.256)	0.497	2.235 (3.164)	0.316
(1, 2, 3, 4, 5, 6, 7) + 8	8.261 (3.774)**	0.497	0.258 (2.449)	0.333
8, 9	113.787 (70.214)	0.168	18.373 (6.785)***	0.508
8, 9, 10	57.904 (52.122)	0.242	9.046 (2.138)***	0.649
8, 9, 10, 11 (1 < K/L < 2)	–96.053 (34.886)***	0.392	11.132 (2.090)***	0.470
(8, 9, 10, 11) + 12	7.879 (4.877)*	0.313	10.732 (1.5686)***	0.509
12, 13	–257.848 (106.274)**	0.825	–36.106 (14.313)**	0.803
12, 14	–2.921 (1.536)*	0.913	–0.339 (0.678)	0.865
12, 13, 14 (K/L > 2)	–0.385 (1.264)	0.827	0.562 (0.576)	0.783
(12, 13, 14) + 11	2.230 (0.960)**	0.371	0.422 (0.589)	0.713

Note: Country code is the one displayed in Table 1.

Table 6. Random-Effects Panel Regressions, Industry Value-Added Share, 7 Countries, 1982-1992

L_i/K_i rank	ISIC code	Capital Intensity (14C)	Capital Intensity (7C)	Effect of ln(*K*/*L*)	Effect of $\ln(w_c/w_{US})$	Between R^2	Within R^2	n
1	322	2.454	1.636	0.003 (0.005)	0.008 (0.003)**	0.034	0.469	77
2	332	4.980	2.296	0.006 (0.001)***	0.001 (0.001)	0.177	0.510	77
3	324	4.126	2.599	0.009 (0.001)***	–0.002 (0.001)***	0.064	0.630	77
4	323	6.969	4.560	0.001 (0.001)**	0.001 (0.0004)***	0.033	0.266	77
5	390	6.591	4.902	0.002 (0.001)**	–0.000 (0.001)	0.2013	0.268	77
6	385	8.658	5.095	–0.001 (0.001)	0.001 (0.0004)***	0.095	0.261	77
7	381	9.173	5.383	–0.002 (0.005)	0.004 (0.003)	0.1057	0.181	77
8	331	9.369	5.642	0.018 (0.007)***	–0.001 (0.004)	0.019	0.213	77
9	382	9.297	6.052	0.001 (0.005)	0.005 (0.003)*	0.026	0.214	77
10	356	10.795	6.402	0.003 (0.003)	0.002 (0.002)	0.049	0.249	77
11	311	11.934	6.519	0.023 (0.014)*	0.011 (0.008)	0.182	0.211	77
12	321	11.317	7.161	0.002 (0.012)	0.007 (0.007)	0.071	0.335	77
13	342	10.167	7.431	0.002 (0.003)	0.005 (0.002)***	0.120	0.305	77
14	383	12.113	8.523	–0.009 (0.008)	0.008 (0.005)*	0.004	0.183	77
15	352	14.184	8.574	–0.022 (0.007)***	0.017 (0.004)***	0.010	0.358	77
16	355	13.327	8.984	–0.004 (0.003)	0.001 (0.001)	0.009	0.138	77
17	384	13.051	9.191	–0.001 (0.007)	0.008 (0.004)**	0.124	0.296	77
18	362	18.708	9.354	–0.002 (0.001)*	0.003 (0.001)***	0.060	0.285	77
19	313	18.223	9.608	0.015 (0.008)*	0.015 (0.004)***	0.234	0.282	77
20	314	19.033	10.057	–0.028 (0.012)**	0.006 (0.006)	0.050	0.331	77
21	361	10.983	10.761	0.001 (0.001)	0.002 (0.001)***	0.351	0.279	77
22	341	21.256	17.577	0.022 (0.004)***	–0.005 (0.002)**	0.161	0.512	77
23	354	30.424	20.533	0.002 (0.004)	0.003 (0.002)	0.375	0.235	77
24	369	26.010	21.060	–0.011 (0.005)**	0.010 (0.003)***	0.094	0.311	77

25	372	29.967	22.271	0.007 (0.020)	0.012 (0.008)	0.387	0.266	69
26	351	38.869	25.174	–0.007 (0.006)	–0.009 (0.004)***	0.361	0.203	77
27	371	37.481	31.692	–0.036 (0.013)***	–0.007 (0.006)	0.435	0.354	69
28	353	98.680	66.305	–0.030 (0.043)	–0.065 (0.020)***	0.120	0.369	77

Note: The third column shows the capital intensity of an industry averaged over the 14 countries, and the fourth column shows the capital intensity of an industry averaged over the seven countries.

Table 7. Random-Effects Panel Regressions, Industry Value-Added Share, 7 Countries, 1982-1992

L_i/K_i rank	ISIC code	Effect of ln(*K*/*L*)	Effect of $\ln(w_c/w_{US})$	Effect of ln(*T*/*Y*)	Between R^2	Within R^2	n
1	322	0.003 (0.005)	0.011 (0.004)***	0.004 (0.002)*	0.194	0.476	77
2	332	0.003 (0.001)***	0.001 (0.0007)*	0.001 (0.0004)***	0.486	0.497	77
3	324	0.007 (0.001)***	–0.002 (0.001)**	0.001 (0.0004)***	0.063	0.678	77
4	323	0.001 (0.0007)*	0.001 (0.0004)**	0.0002 (0.0002)	0.070	0.259	77
5	390	0.002 (0.001)**	–0.0004 (0.001)	0.0002 (0.0003)	0.082	0.262	77
6	385	–0.001 (0.001)	0.001 (0.0004)***	–0.001 (0.0004)*	0.182	0.288	77
7	381	–0.001 (0.004)	0.004 (0.003)	0.003 (0.002)	0.344	0.199	77
8	331	0.014 (0.007)**	0.001 (0.004)	0.006 (0.002)***	0.248	0.261	77
9	382	0.0002 (0.005)	0.005 (0.003)*	0.002 (0.002)	0.042	0.226	77
10	356	0.004 (0.004)	0.002 (0.002)	–0.001 (0.002)	0.051	0.252	77
11	311	0.027 (0.015)*	0.011 (0.008)	0.006 (0.008)	0.259	0.212	77
12	321	–0.007 (0.012)	0.018 (0.008)**	0.028 (0.008)***	0.493	0.418	77
13	342	–0.0003 (0.002)	0.006 (0.001)***	0.004 (0.001)***	0.678	0.350	77
14	383	–0.003 (0.007)	0.009 (0.005)**	0.011 (0.003)***	0.039	0.322	77
15	352	–0.016 (0.007)**	0.018 (0.004)***	0.012 (0.004)***	0.022	0.442	77
16	355	–0.003 (0.003)	0.001 (0.001)	0.004 (0.002)**	0.008	0.225	77
17	384	0.0003 (0.007)	0.009 (0.004)**	0.0004 (0.003)	0.230	0.304	77
18	362	–0.002 (0.001)	0.003 (0.001)***	0.001 (0.001)	0.191	0.302	77
19	313	0.016 (0.008)**	0.015 (0.004)***	0.004 (0.002)*	0.329	0.312	77
20	314	–0.045 (0.013)***	0.004 (0.006)	0.008 (0.003)***	0.001	0.416	77
21	361	0.001 (0.001)	0.002 (0.001)***	0.0008 (0.0003)**	0.256	0.352	77
22	341	0.021 (0.004)***	–0.005 (0.002)**	–0.0004 (0.001)	0.151	0.513	77
23	354	0.004 (0.004)	0.001 (0.002)	–0.001 (0.001)	0.200	0.278	69
24	369	–0.012 (0.004)***	0.009 (0.002)***	0.004 (0.001)***	0.498	0.391	77
25	372	0.025 (0.018)	0.029 (0.009)	0.015 (0.006)***	0.868	0.113	69

26	351	–0.005 (0.006)	–0.008 (0.004)**	0.004 (0.003)	0.290	0.232	77
27	371	–0.034 (0.013)***	–0.010 (0.006)*	–0.007 (0.004)*	0.457	0.393	69
28	353	–0.030 (0.043)	–0.069 (0.019)***	–0.031 (0.014)	0.054	0.408	66