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Specialization, Factor Accumulation and Development

Doireann Fitzgerald and Juan Carlos Hallak

Harvard University

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Abstract

The Heckscher-Ohlin theory links specialization of production to relative factor endowments. Endowments are the result of accumulation in response to economic incentives. Taking this into account allows us to reconcile wildly different predictions in the empirical literature about the effect of capital accumulation on manufacturing output. We estimate the effect of factor proportions on specialization in a cross-section of OECD countries. We show that using the estimation results alone, we cannot distinguish between specialization driven by factor proportions, and specialization that is correlated with factor proportions for other reasons. But our results are consistent with evidence on sectoral factor intensities, which supports the H-O theory. Moreover, our model does a good job of predicting the substantial reallocation that takes place within manufacturing as countries grow. It explains 2/3 of the observed difference in the pattern of specialization between the poorest and richest OECD countries.

1 Introduction

The Heckscher-Ohlin (H-O) theory states that differences in the patterns of specialization across countries are determined by differences in their factor endowments. It answers the

*Department of Economics, Littauer Center, Cambridge, MA 02138. dfitzger@kuznets.harvard.edu and jhallak@kuznets.harvard.edu. We are particularly grateful to Elhanan Helpman and Kenneth Rogoff for their guidance and encouragement. We also thank Julio Berlinski, Dale Jorgenson, Edward Leamer, Greg Mankiw, Marc Melitz, Jaume Ventura, and seminar participants at Harvard University and MIT for helpful comments. The usual disclaimer applies.

crucial question of what explains trade between countries by focusing on the determinants of sectoral specialization.[1] The dominance of this theory during the last decades has motivated several studies attempting to assess its empirical relevance. In particular, in the last decade a number of studies have estimated the effect of changes in factor endowments on the pattern of specialization. These studies arrive at contradictory results and do not provide a consistent picture of how factor endowments affect specialization. In this paper, we reconcile these contradictory results by taking into account that relative factor endowments are determined by the accumulation of physical and human capital in response to economic incentives. We estimate the effect of relative factor endowments on specialization within manufacturing using a cross-section of OECD countries that are at different levels of development. We cannot always identify with precision the separate effects of physical and human capital accumulation on specialization, as these factors are strongly correlated with each other by virtue of the common accumulation process. In fact, since the identification of the empirical model comes mainly from cross-country differences in levels of development, we are unable to distinguish between the H-O theory and alternative theories that link specialization and development using our estimation results alone. However, when significant, the estimated effects of individual factors are consistent with evidence on sectoral factor intensities, which is in favor of H-O. Moreover, factor endowments do a good job of predicting the pattern of specialization within the OECD. Moving from the poorest quartile of OECD countries to the richest quartile entails reallocation within manufacturing as a whole of over 13% of GDP. Our model correctly predicts 2/3 of this reallocation.

The empirical literature on factor endowments and specialization follows two main strands. The majority of the studies in the first strand motivate their estimation strategy by focusing on a very particular case of the theory that predicts a linear relationship between sectoral output and factor endowments - the Rybczynski equations. This requires factor price equalization (FPE) between countries, and that the number of goods equals the number of factors. These equations have been estimated by Harrigan (1995), Davis and Weinstein (1998), Reeve (1998), and Bernstein and Weinstein (2002). Other studies in this strand of the literature

[1] As many economists in the field have noted, the "intellectual capital" of the H-O theory is mainly on the production side.

relax the assumption of FPE [Leamer (1987) and Schott (1999)]. But a common theme in the motivation and estimation is the assumption that all countries have access to the same technology. A striking regularity in the results is that capital accumulation is estimated to have a positive and statistically significant impact on output in almost all manufacturing sectors. Meanwhile the effect of changes in the endowments of other factors cannot in general be estimated with precision.

The second strand in the empirical literature is represented by Harrigan (1997) and Harrigan and Zakrajšek (2000). This strand differs substantially in the framework used to derive the empirical specification linking factor endowments to specialization. In particular, it allows countries to differ in their productivity levels, and the identification comes mainly from within-country across-time variation. This strand of the literature makes predictions about the effect of endowment changes on specialization that are quite different from those just described. The effect of capital accumulation on specialization is no more precisely estimated than the effect of changes in other factor endowments. Increases in the capital stock are not systematically associated with increased production in most manufacturing sectors. The economic implications of these two different sets of results are quite different. Results in the Rybczynski tradition suggest that as a country accumulates capital, almost all manufacturing sectors continue to grow. Results from the second strand of the literature suggest substantial reallocation across manufacturing sectors as capital accumulates.

In the second section of the paper, we briefly lay out the particular case of the H-O theory used to derive the Rybczynki equations. We estimate these equations for 25 manufacturing sectors using a cross-section of 21 OECD countries in 1988 and reproduce the results of the previous literature. In particular, we get a significantly positive coefficient on capital in almost all of our manufacturing sectors. We present evidence on sectoral factor intensities that is at odds with this particular feature of the results.

In Section 3, we explain how the failure to account for cross-country productivity differences biases the estimation. The bias arises because productivity levels affect incentives for factor accumulation. Since relative productivity is persistent over time, endowments of accumulable factors and productivity levels are strongly positively correlated. The omission of productivity differences from the estimated model leads to a form of omitted variable bias.

In particular, we argue that the omission tends to bias upwards the estimated coefficient on capital. We introduce Hicks-neutral productivity differences into the theoretical framework, and derive productivity-adjusted Rybczynski equations. When we estimate these equations, we find that the coefficient on capital is no longer almost uniformly significantly positive. This goes a substantial way towards reconciling the results of the Rybczynski literature with the other strand in the empirical literature.

In Section 4 we discuss the extent to which the results in the previous section can be interpreted in the light of a less restrictive version of the Heckscher-Ohlin theory that links specialization (sectoral shares in GDP) to factor proportions (*relative* factor endowments). We show that a simple transformation of the model in Section 3 is very similar to a reduced form that captures the spirit of the Heckscher-Ohlin theorem. We estimate this reduced form, and find that the results are consistent with evidence on factor intensities across sectors, although we are not always able to estimate with precision the independent effects of particular factor ratios on specialization. We explore the similarities between our results and those of Harrigan and Harrigan and Zakrajšek. Despite stark differences in identification strategies, the results are broadly comparable.

In section 5, we consider the links between development, accumulation and specialization. We show that within our sample, factor proportions and specialization are both strongly correlated with the level of development. Differences in level of development are the main source of identification in our data. This explains why we cannot always identify with precision the independent effects of different factor proportions on the sectoral distribution of production. It also raises the possibility that forces other than Heckscher-Ohlin can explain the results. Using our data, we cannot reject the possibility that these alternative forces drive the observed correlation between relative factor abundance and specialization. But the fact that the results are consistent with evidence on factor intensities across sectors suggests that the Heckscher-Ohlin mechanism is still the driving force. We can then show that a substantial fraction of the difference in patterns of specialization between countries at different stages of development can be explained by differences in factor proportions. To do this, we rank countries in our sample according to income per capita and select the top and bottom quartiles. The actual difference in patterns of manufacturing specialization between the two groups amounts to a reallocation of over 13% of GDP. We use our factor endowments model to predict the differences in manufacturing specialization. We find that differences in factor proportions can explain 2/3 of the difference in the patterns of specialization between the two groups. This suggests that differences in factor proportions play an important role as determinants of specialization, even for OECD countries.

2 The Rybczynski Framework

This section outlines the theory that motivates the literature on endowments and specialization that has estimated Rybczynski equations. We reproduce the results of this literature using our data-set. These estimates will serve as a benchmark. We examine them in some detail, and explain why we find them puzzling. This motivates the improvements in estimation and interpretation that we propose in the following sections.

2.1 Theory and Empirical Implementation

Assume gross output of sector j in country c, y_j^c, can be written as a neoclassical constant returns to scale function of factor inputs and intermediate inputs:

$$y_j^c = f_j^c\left(\widetilde{\mathbf{v}}_j^c, \mathbf{m}_j^c\right) \tag{1}$$

where $\widetilde{\mathbf{v}}_j^c$ is a vector of factor inputs and $\mathbf{m}_j^c$ a vector of intermediate inputs. Given perfect competition in input and output markets, the solution to the unit cost minimization problem for producers in sector j and country c can be expressed as:

$$\widetilde{z}_j^c = g_j^c(\widetilde{\mathbf{w}}^c, \mathbf{p}^c) \tag{2}$$

where $\widetilde{z}_j^c$ is the vector of unit input requirements, $\widetilde{\mathbf{w}}^c$ is the vector of factor prices and $\mathbf{p}^c$ is the vector of goods prices (including intermediate goods).

Assume also that technology is identical in all countries ($f_j^c = f_j$ and $g_j^c = g_j$), the law of one price holds in goods markets ($\mathbf{p}^c = \mathbf{p}$), and there is factor price equalization

$(\widetilde{\mathbf{w}}^c = \mathbf{w})$. Then, $\widetilde{z}_j^c = \widetilde{z}_j$. That is, unit factor input requirements and unit intermediate input requirements are the same across countries. Denote $\widetilde{b}_{fj}$ the unit input requirement of factor f in sector j. Stacking, we get the unit direct factor input requirement matrix, $\widetilde{B}$, common to all countries:

$$\widetilde{B} = \begin{bmatrix} \widetilde{b}_{11} & \cdots & \widetilde{b}_{1J} \\ \vdots & \ddots & \vdots \\ \widetilde{b}_{F1} & \cdots & \widetilde{b}_{FJ} \end{bmatrix}$$

Market clearing requires that

$$\widetilde{B}\mathbf{y}^c = \widetilde{\mathbf{v}}^c \tag{3}$$

hold in every country, where $\mathbf{y}^c$ is the vector of gross output of country c and $\widetilde{\mathbf{v}}^c$ is its vector of factor endowments. If there are the same number of goods and factors $(J = F)$, $\widetilde{B}$ is invertible. Let $\widetilde{B}^{-1} = R$. This yields

$$\mathbf{y}^c = R\widetilde{\mathbf{v}}^c \tag{4}$$

That is, there is a linear relationship between gross output and factor endowments, the parameters of which can be estimated by running sector by sector linear regressions of country gross output in the sector on country factor endowments. These are known as Rybczynski equations. Since unit input requirements of both direct factors and intermediate inputs are common across countries, in each sector the share of value added in gross output is also common across countries. This implies that (3) also holds when $\mathbf{y}^c$ is the vector of sectoral value added instead of gross output. In that case, $\widetilde{B}$ is the matrix of direct factor input requirements per unit of value added.

Rybczynski equations can be empirically implemented by estimating

$$\mathbf{y}_j = V\mathbf{r}_j + \boldsymbol{\epsilon}_j \tag{5}$$

for each sector j. One very strong assumption in the derivation of (4) is that there is an equal number of goods and factors $(J = F)$. If $J > F$, the matrix $\widetilde{B}$ is not invertible and production is indeterminate. If $J < F$, factor price equalization (FPE) is not attained, and production cannot be written as a unique function of endowments.[2] Given that in the data there are more sectors than factors, the usual structural interpretation of the error term is that it captures the effect of omitted factors. It also captures random disturbances to sectoral production, assumed uncorrelated with the regressors. A constant term is typically included to pick up a non-zero mean of the error term.The variance of the error is correlated with country size, so a correction for heteroskedasticity is desirable. Endogenous heteroskedasticity corrections give unsatisfactory results here because they are driven by a big outlier in size: the US (Reeve 1998). Instead, the literature on Rybczynski equations weights the observations by the inverse of GDP or its square root. We use the inverse of GDP to weight. The pattern of results is insensitive to which is chosen. It is also insensitive to the inclusion or exclusion of a constant term. For ease of exposition we will report the results without a constant term.

2.2 Data

Here we briefly describe the data we use. The details are given in Appendix A. All data are for 1988. Our sample consists of 21 OECD countries.[3] We restrict ourselves to OECD countries because many of the assumptions of the Rybczynski framework, such as FPE and the absence of trade costs, are less reasonable for a larger sample than they are for the OECD. GDP data come from the OECD, and sectoral production data from UNIDO. Our sectoral production data consist of gross output and value added in 25 3-digit ISIC manufacturing sectors, converted into dollars using market exchange rates. We consider the data on gross output to be of better quality than the data on value added. Also, gross output is the production measure used by previous research. On the other hand, as will become clear later, the results using value added have a more straightforward interpretation. We choose value added as our baseline. For space reasons, we do not report the results using gross output, but we describe them in the text. Special attention is given to the gross output results in this section, where we reproduce the findings of the previous literature. In most cases, the results are very similar.

[2] See Harrigan (2001) for an extensive discussion of the different cases.

[3] We use all countries in the OECD in 1988, except for Iceland and Luxemburg, excluded because of their size, and Switzerland, excluded because sectoral production data is very incomplete.

There are four factors in our data set: capital, skilled labor, unskilled labor and arable land. Data on the capital stock come from the Penn World Tables (PWT). We use non-residential capital as our baseline measure of the capital stock. It is the sum of producer durables and nonresidential construction. The labor force also comes from the PWT. It is divided into skilled and unskilled labor using data from the OECD on educational attainment. Workers who have at least some senior cycle second level education are considered skilled. The rest of the labor force is considered unskilled. Arable land comes from FAO.

Summary statistics of sectoral value added shares are given in Table 1. They show that there are indeed cross-country differences in production structure. Endowment data are reported in Table 2. We will interpret this table in more detail later. Country abbreviations are self-explanatory apart from Australia (AUS) and Austria (AUT).

2.3 Results

The results from estimating (5) using value added as the dependent variable are reported in Table 3. As explained, the results are not sensitive to the inclusion or exclusion of a constant term, and we present here the results without a constant. We draw particular attention to the coefficient on capital. This coefficient is positive in all but two sectors (*Tobacco* and *Professional and scientific equipment*). In 14 out of 25 sectors it is significantly positive. The coefficients on skilled and unskilled labor do not follow a uniform pattern. The coefficient on skilled labor is significantly positive in only 9 sectors and significantly negative in 2 sectors. The coefficient on unskilled labor is significantly positive in 3 sectors and significantly negative in 3 sectors. The coefficient on land is almost always negative, and significantly negative in 6 sectors. Since the regressions do not include a constant, we do not report R^2s. Instead, we report the average prediction error (APE), for each equation, and for the system as a whole.[4] The APE for our system is 70%, similar to that obtained by others who have estimated these equations.

When we use gross output instead of value added, the signs of the coefficients are almost

[4]The prediction error for an observation is calculated as $PE = \frac{|\hat{y}-y|}{y}$. The APE for an equation is the average over all observations used to estimate it. The APE of the system is the average over observations for all sectors and countries.

unchanged. In particular, the coefficient on capital is positive in all but one sector and significantly positive in 18 sectors. The coefficient on skilled labor is significantly positive in only 4 sectors. The pattern of results for the other two factors is largely unchanged. The APE for the system is 65%. These results are almost identical to those obtained by other researchers using gross output data of OECD countries. Harrigan (1995), Davis and Weinstein (1998), Bernstein and Weinstein (1998), and Reeve (1998) all get coefficients on capital that are almost always positive, and significantly positive in most cases. No such systematic pattern is evident for the other factors. Increases in the capital stock are also associated with increases in production in most manufacturing sectors in Leamer (1987) and Schott (1999), who work with larger samples of countries, and do not assume a uni-cone model.

The results in Table 3, like those in the previous literature, show that factor endowments help predict sectoral output across countries. But looking more closely at the estimated coefficients, the results are puzzling. A positive Rybczynski coefficient on capital in a particular sector indicates that an increase in the aggregate supply of capital will raise output in that particular sector. The only constraint the theory imposes on these coefficients is that, as a factor increases, there is at least one sector that will contract and one that will expand proportionally more than the factor increase. This constraint is not violated. However, the estimated coefficients are not consistent with evidence on factor intensity for the various manufacturing sectors, in particular with the evidence on capital intensity. Table 4 shows for the US the relative capital-labor ratio for each of our sectors, and the percentage of the labor force in each sector that is skilled and unskilled. The ranking of sectors is similar for other countries we have examined. Even though the theory does not predict a one-to-one correspondence between capital intensity and the Rybczynski coefficient, on average we should expect more positive coefficients in sectors that use capital more intensively. But there are large and significantly positive Rybczynski coefficients in the three sectors with the lowest capital-labor ratios (*Apparel*, *Leather products*, and *Footwear*) while in some of the sectors with the highest capital-labor ratios (for example, *Tobacco* and *Iron and steel*) the estimated Rybczynski coefficients are statistically indistinguishable from zero. In the case of skilled and unskilled labor, the results are much more consistent with the evidence on factor intensity, but fewer of the estimated Rybczynski coefficients are significantly positive or significantly negative.

3 Productivity differences and econometric bias

A central assumption of the Heckscher-Ohlin model is that technology is identical across countries. However, the evidence points overwhelmingly to the fact that technology differences across countries are empirically important. In the growth literature, Islam (1995, 1999), Conrad and Jorgenson (1995), Klenow and Rodriguez-Clare (1997), Dougherty and Jorgenson (1999), and Hall and Jones (1999) estimate TFP for several countries and find that productivity differences across countries are large, even between the most advanced developed economies. In the trade literature, Trefler (1995) and Davis and Weinstein (2001) find that accounting for productivity differences significantly improves predictions of the factor content of trade.

Productivity differences show up clearly in our data. Table 2 shows factor abundance for each factor and country in our sample. The measure of factor abundance is $\left(v_f^c/Y^c\right)/\left(v_f^w/Y^w\right)$, where Y denotes GDP, and the superscript w denotes the world (i.e., all the countries in the sample). As argued by Leamer (1984), these resource abundance ratios, frequently used in the HOV literature, are a useful indicator of factor abundance when GDP is a linear function of endowments. A coefficient greater than one indicates that a factor is relatively abundant and a coefficient less than one that it is relatively scarce. Rich countries (such as Sweden) appear to be scarce in all factors because output is high relative to endowments. Poor countries (such as Turkey and Greece) appear to be abundant in all factors because output is low relative to endowments. This is Trefler's (1995) "endowments paradox".

In the rest of this section, we describe how productivity differences may be introduced into the framework we have outlined so far. We explain how the failure to correct for productivity differences leads to systematically biased results. We construct measures of productivity, and estimate Rybczynski equations taking account of cross-country productivity differences. We compare the new results to those in the previous section and confirm that the systematic bias we describe is important.

3.1 Productivity-adjusted model

Suppose that differences in technology across countries can be represented as factor-specific productivity differences. One unit of factor f in country c is equivalent to a_f^c units of that factor in a numeraire country. Re-interpret the variables with tildes in Section 2.1 as corresponding to factors measured in efficiency units. Then $\widetilde{\mathbf{v}}_j^c = A^c \mathbf{v}_j^c$, where A^c is a diagonal matrix composed of factor-specific productivities,

$$A^c = \begin{bmatrix} a_1^c & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_F^c \end{bmatrix}$$

and $\mathbf{v}_j^c$ is the vector of unadjusted factors. The vector of returns to efficiency units of factors is $\widetilde{\mathbf{w}}^c$.

Assume that the production function in adjusted factors is the same across all countries. Assume that the law of one price holds. Also, following Trefler (1993), assume that conditional factor price equalization holds. That is, it is rewards to *efficiency units* of factors that are equalized across countries: $\widetilde{\mathbf{w}}^c = \mathbf{w}$ (note that $\mathbf{w}^c = A^c \mathbf{w}$). Then, efficiency-equivalent unit input requirements for each industry are the same across countries. These $\widetilde{b}_{fj}$ can be stacked to form $\widetilde{B}$, the unit direct efficiency-equivalent factor input requirement matrix, common to all countries. Denoting $R = \widetilde{B}^{-1}$, we obtain a linear relationship between output and efficiency-equivalent factors. This is the system of productivity-adjusted Rybczynski equations:

$$\mathbf{y}^c = R\widetilde{\mathbf{v}}^c = RA^c\mathbf{v}^c$$

This relationship can be estimated by regressing output on efficiency-equivalent factors.

Hicks-neutral productivity differences are the particular case where $a_f^c = a^c$ for all f. Trefler (1995) and Davis and Weinstein (2001) provide evidence that Hicks-neutrality is a good first-order approximation to true differences in technology across countries. We assume Hicks-neutral differences in technology. Under the assumption of Hicks-neutrality, the adjusted Rybczynski relationship is

$$y_j^c = r_{j1} a^c v_1^c + \ldots + r_{jF} a^c v_F^c + \epsilon_j^c \tag{6}$$

where the $a^c v_f^c$ are efficiency-equivalent factor endowments. As before, a constant term in this equation would pick up the average effect of omitted productivity-adjusted factors. Size-related heteroskedasticity can be controlled for by weighting the observations by the inverse of GDP.

3.2 Econometric bias

Before estimating this new specification, we show that if productivity differences are not accounted for, the estimated Rybczynski coefficients are subject to a form of omitted variable bias. Suppose there are productivity differences across countries, so the true model is

$$y_j^c = \mathbf{v}_j^{c\prime} a^c r_j + \epsilon_j^c. \tag{7}$$

Consider what happens when we ignore the a^cs and estimate instead

$$y_j^c = \mathbf{v}_j^{c\prime} r_j + \theta_j^c \tag{8}$$

Adding and subtracting $\mathbf{v}_j^{c\prime} r_j$ from (7), the true model can be re-expressed as:

$$y_j^c = \mathbf{v}_j^{c\prime} r_j + (a^c - 1)\, \mathbf{v}_j^{c\prime} r_j + \epsilon_j^c. \tag{9}$$

From (8) and (9), $\theta_j^c = (a^c - 1)\mathbf{v}_j^{c\prime} r_j + \epsilon_j^c$. The error term θ_j^c in the estimated model is hence correlated with the independent variables (unless $a^c = 1$ for all c). This leads to biased estimates of the R matrix. We call this the productivity bias.

There are reasons to expect that this bias will be systematic. The error term θ_j^c will tend to be large for more productive countries ($a^c > 1$), and small for less productive countries ($a^c < 1$). A standard result in traditional growth models is that more productive countries face greater incentives to accumulate capital relative to their labor endowments. If productivity differences are correlated across time, countries which are now more productive will have been more productive in the past and as a result will have accumulated more capital relative to other factors. This would imply that in the cross-section, more productive countries would be more capital-abundant. This would lead measured capital endowments and the error term to be positively correlated, biasing upwards the estimated coefficient on capital.

There is a positive correlation between capital and productivity in our sample. It is also an empirical regularity in bigger samples of countries.[5] This suggests that the productivity bias is driving the finding in the literature that the coefficient on capital is positive and significant in most manufacturing sectors. Market incentives also affect skilled labor accumulation, though the impact is probably weaker than on physical capital accumulation. In our sample there is a positive correlation between skilled labor and productivity. However, it is weaker than for capital. This could explain why the productivity bias does not appear to drive the coefficient on skilled labor across sectors and across studies as it does for capital.[6]

Three independent pieces of evidence are consistent with an upward bias on the coefficient on capital in estimates of standard Rybczynski equations due to the omission of productivity differences. First, Bernstein and Weinstein (1998) estimate equation (5) for a sample of OECD countries and for Japanese regions. In the case of Japan, (in contrast to the OECD) the coefficient on capital is not positive and significant in most manufacturing sectors. This is plausibly explained by the fact that technology differences across Japanese regions (in contrast to OECD countries) are small, and hence the bias is small. Second, Harrigan (1997) and Harrigan and Zakrajšek (2000) examine the role of factor endowments as determinants of production allowing for productivity differences. They do not find the coefficient on capital positive and significant in most manufacturing sectors. Finally, Turkey is an outlier in our sample in terms of productivity. When we exclude it from the estimation, the strong pattern

[5] Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) provide evidence of a strong positive correlation between TFP and K/L ratios for over 90 countries.

[6] Harrigan (1995) gets positive and significant coefficients on capital when he runs the Rybczynski regression on a panel with fixed effects. In this case, the productivity bias does not work through the channel we have just described. It probably arises because productivity is determined by capacity utilization. During an expansion, factors are working at or near full capacity, so output is high relative to measured endowments. At the same time, investment is also high. With a high depreciation rate (13.3%), the capital stock is sensitive to the investment rate. Thus, it is more correlated with the business cycle than other factors are.

of positive and significant coefficients on capital is considerably attenuated.

3.3 Hicks-neutral productivity

In order to estimate (6) we need a measure of TFP (or a^c) for each country. We choose a TFP measure that is consistent with our measures of factor endowments and with the hypothesis of conditional factor price equalization. Conditional factor price equalization and Hicks-neutrality together imply that for all factors f,

$$w_f^c = a^c w_f^{US}$$

where w_f^{US} are returns to factor f in the numeraire country (the US) for which $a^{US} = 1$. Within the set of countries for which conditional FPE holds, and for given goods prices, the revenue function is linear in factor endowments:

$$Y^c = \sum_{f=1}^{F} v_f^c w_f^c = a^c \sum_{f=1}^{F} v_f^c w_f^{US}.$$

Hence, if we know the factor returns in the US, we can calculate a^c as

$$a^c = \frac{Y^c}{\sum_{f=1}^{F} v_f^c w_f^{US}} \tag{10}$$

To calculate TFP in this way, we need data on US factor returns. We calculate factor returns for the US by dividing total factor income for each factor in 1988 by the relevant factor endowment. The construction of total factor income is described in Appendix B. We report the FPE-consistent measure of TFP in the first column of Table 5. We use our TFP estimates to construct efficiency-equivalent measures of factor abundance i.e. $\left(\tilde{v}_f^c/Y^c\right) / \left(\tilde{v}_f^w/Y^w\right)$. These are reported in the last four columns of Table 5. By construction, the endowments paradox is not present in these measures. The last row of Table 5 shows the correlation between TFP and these measures of factor abundance. There is a strong positive correlation (0.83) between productivity and capital abundance, and a positive but weaker correlation between productivity and skilled labor abundance.

3.4 Results

Table 6 gives the results from estimating equation (6). We correct for heteroskedasticity by weighting observations by the inverse of GDP. As in the unadjusted case, the inclusion or exclusion of a constant does not affect the results. We report the no-constant regression. The coefficient on capital is no longer positive in almost all sectors. Moreover, it is never significantly positive and it is significantly negative in two sectors (*Textiles* and *Industrial chemicals*). The coefficient on skilled labor is significantly positive in 17 sectors out of 25, and the coefficient on unskilled labor is significantly positive in 13 sectors out of 25. There are no negative and significant coefficients for either skilled or unskilled labor. These results contrast strongly with those from estimating the unadjusted model. As before, the coefficient on land is often negative, and in three cases significantly negative. The APE for the system is 60%, a reduction of 10 percentage points compared with the unadjusted model. When we use gross output instead of value added, the results are very similar. There is only one positive and significant coefficient for capital (Non-ferrous metals), and no negative and significant coefficients for that factor. The coefficient on skilled labor and unskilled labor are positive and significant in 16 and 15 sectors, respectively. The APE for the system is 57%.

The introduction of productivity differences changes the results dramatically. In the case of capital, the direction of the change is consistent with productivity differences biasing upwards the coefficient on capital. The magnitude of the change indicates that the bias is important. The coefficient on capital is lower than in the unadjusted model in every sector but one (Non-ferrous metals). From the point of view of prediction, these results are also an improvement. The average prediction error falls in 22 out of 25 sectors, and the average prediction error of the whole system also falls. However, some features of the new results are still puzzling. Most of the coefficient signs on skilled and unskilled labor are positive, and all of the significant coefficients on these two factors are on positive estimates. We now show that some unattractive features of the Rybczynski specification drive these puzzling features.

4 From Rybczynski to a H-O reduced form

The Heckscher-Ohlin theorem links factor abundance, factor intensities and the pattern of specialization (and trade). The spirit or intuition of the theorem is that countries will on average produce (and export) more in those sectors that use intensively the factors in which they are relatively abundant. The underlying mechanism links autarky factor prices to relative factor abundance. In turn, factor intensities and autarky factor prices together determine autarky goods prices. Relative prices of goods in autarky determine comparative advantage, and hence specialization in production and trade. The H-O intuition can be easily formalized in the 2x2x2 case. However, in its classic generalized formulation [Deardorff (1982)], it does not yield empirical predictions at the sectoral level. The main prediction is about an average across all sectors. Recent work by Romalis (2002) has however provided a useful formalization of the H-O intuition in a quite general case. In the presence of imperfect competition and trade costs, the Heckscher-Ohlin link between factor abundance, factor intensities and trade (or specialization) applies not only as an average across sectors, but also to individual sectors. Even though he cannot write down a closed-form solution, his theoretical results give a foundation for a sector-by-sector reduced-form regression of specialization on relative factor endowments.

The Rybczynski equations focus on the relationship between factor abundance and specialization in the case where factor prices are equalized, and there are the same number of goods and factors. Their appeal in the empirical literature on explaining specialization arises from the fact that they predict an exact linear relationship between observables in a field where exact predictions are rare. But they have two major disadvantages. First, the theoretical assumptions that underlie the derivation are very strong. By introducing productivity differences and assuming conditional rather than absolute factor price equalization, we have been able to relax one assumption. But even conditional FPE is unlikely to hold strictly for our sample. There are costs to trade, and factor endowments may be sufficiently different that there is more than one cone of specialization. It would also be an unlikely coincidence to have the same number of goods as factors. All of these assumptions must hold exactly to give the knife-edge linear Rybczynski specification. Since it is likely that at least some of them are violated, it is hard to know how to interpret the estimated coefficients. Second, the Rybczynski equations are a linear relationship between *levels* of production and *levels* of factor endowments. They tell us the impact of an increase in the stock of one factor on the level of production in a particular sector. But in its more general form, the H-O theorem predicts a relationship between *relative* factor abundance and the pattern of specialization, i.e. sectoral *shares* in total output. Rybczynski equations are hard to interpret because it is hard to carry our H-O intuition over to a relationship between levels.

So can we still learn something about H-O from estimating Rybczynski coefficients? In this section, we first show that the specification we have used so far is subject to scale effects and linear dependence of regressors. This leads us to re-specify the Rybczynski equations. This new specification is very close to an intuitively appealing reduced form for examining the relationship between specialization and relative factor endowments. We estimate both and get similar results. We compare the results with evidence on sectoral factor intensities. In this light, the estimated coefficients are consistent with the Heckscher-Ohlin intuition.

4.1 Scale effects and linear dependence

In the previous section we estimated (6), weighting each observation by the inverse of GDP to control for heteroskedasticity. This is equivalent to estimating

$$\frac{y_j^c}{Y^c} = \sum_{f=1}^{F} r_{jf} \frac{\tilde{v}_f^c}{Y^c} + \epsilon_j^c \tag{11}$$

At face value, this looks like a reasonable linear approximation to a relationship between specialization and relative factor endowments. On the left is a measure of specialization (sectoral shares of GDP) and on the right are measures of relative factor endowments.[7] However, there are two problems with interpreting (11) as a reduced form. First, the estimates may be driven by scale effects due to the absence of a constant term. Second, there is a problem of linear dependence in the measures of relative factor abundance.

Without a constant in (11), even if relative factor endowments do not drive the pattern

[7] These are the resource abundance ratios we mentioned before. They are now corrected for productivity, and they are not scaled by the world factor-to-GDP ratio.

of specialization we would not expect all the estimated coefficients to be zero. Mechanically, some coefficients would have to be positive because both the dependent variable and the independent variables are always positive. We cannot distinguish coefficients that are significantly positive for this reason (the absence of a constant) from coefficients that are significantly positive because an increase in a factor supply has a positive effect on output. We call this a scale effect because the equivalent problem in the level equation representation (6) is that some estimated coefficients are biased upwards as large countries have large endowments and also produce more in all sectors.[8]

However, we cannot include a constant because by construction, a linear combination of the independent variables sums to one:

$$1 = \sum_{f=1}^{F} w_f^{US} \frac{\tilde{v}_f^c}{Y^c},\ \forall c$$

As a result there is perfect multicollinearity between our measures of relative factor abundance and an unweighted constant. We could avoid this problem by constructing productivity in a different way. But the fact that we have used this particular relationship to construct our baseline productivity measure points to the second fundamental difficulty in interpreting (11) in the spirit of the Heckscher-Ohlin theory. The problem is that with F factors, we can have at most $F-1$ independent measures of relative factor abundance. There can be no independent variation in the regressors.

In order to address the scale effect and linear dependence, we correct for heteroskedasticity weighting by the productivity-adjusted labor force ($a^c L^c$) instead of GDP. The correlation between productivity-adjusted labor force and GDP in our sample is very high (0.99), so weighting by productivity-adjusted labor is ex-ante as reasonable as weighting by GDP. Instead of (11), we obtain:

$$\frac{y_j^c}{a^c L^c} = r_{jK}\frac{K^c}{L^c} + r_{jS}\frac{S^c}{L^c} + r_{jU}\frac{U^c}{L^c} + r_{jA}\frac{A^c}{L^c} + \epsilon_j^c$$

[8]Including a constant in the level equation (6) does not deal with the scale effect, as a constant does not vary with country size. A constant in (6) shows up as a weighted "constant" (r_{j0}/Y^c) in (11), which does not help either as it is not a "true" constant. Its inclusion in the estimation has a negligible effect on the results and it is not significantly different from zero.

The linear dependence problem is now very explicit. By definition, $L^c = S^c + U^c$, so $\frac{S^c}{L^c} + \frac{U^c}{L^c} = 1$. It is clear that we cannot identify separately the effects of increases in the skilled labor share and decreases in the unskilled labor share. So we rewrite the equation as

$$\frac{y_j^c}{a^c L^c} = r_{jU}^c + r_{jK}\frac{K^c}{L^c} + (r_{jS} - r_{jU})\frac{S^c}{L^c} + r_{jA}\frac{A^c}{L^c} + \epsilon_j^c \tag{12}$$

The independent variables are capital per worker, the share of skilled labor in total labor, and arable land per worker - typical factor proportions in the trade literature. For four factors, there are only three measures of relative factor abundance.[9] We note two things about this transformed Rybczynski specification. First, we do not need to estimate (12). The results can be recovered from the results of (6) if it is estimated using weights proportional to adjusted labor.[10] Second, the productivity bias is not present. The productivity correction appears in the adjustment of labor on the LHS.

However, the dependent variable in (12) does not have an appealing reduced form interpretation. A more appealing reduced form would have output in sector j as a share of total GDP as a dependent variable

$$\frac{y_j^c}{Y^c} = \beta_{jU}^c + \beta_{jK}\frac{K^c}{L^c} + \beta_{jS}\frac{S^c}{L^c} + \beta_{jA}\frac{A^c}{L^c} + \epsilon_j^c \tag{13}$$

As we just pointed out, the correlation between productivity-adjusted labor force and GDP is in fact very high. In consequence, the results from estimating (13) turn out to be very similar to those from estimating (12). We can thus interpret a transformation of the Rybczynski coefficients as the effect of differences in factor proportions on the pattern of specialization. This provides a link between a structural specification derived from a knife-edge case, and an appealing linear approximation to a more general version of the H-O theory. The reduced form specification has the advantage that it does not depend on how productivity is measured, as the effect of productivity is captured by GDP. If the assumptions of the Rybczynski theory hold, then (12) is the right specification and (13) is (slightly) mispecified. If they do

[9] In his 1987 paper on paths of development, Leamer includes the first and third measures in a similar regression, though he does not make the productivity adjustment on the left hand side.

[10] The covariance matrix of the estimated coefficients in (6) is also needed to recover (12) from (6).

not hold, then one specification is just as valid as the other as an approximation. But (13) is preferable because the results have a more straightforward interpretation.

4.2 Results

Now that we have specifications that eliminate the productivity bias, the scale effect and linear dependence, we interpret in detail the actual coefficient estimates. The results from estimating (12) and (13) are reported in Table 7 and Table 8, respectively. Although the dependent variable is different in each case, the results are remarkably similar, and we focus on the reduced form (13) estimation in Table 8. Overall, the results are in line with the evidence on factor intensities in the different sectors. They also provide a clear and plausible picture of how relative factor endowments affect specialization within the countries in our sample. They can be interpreted more structurally if we do not reject the restrictive assumptions of the Rybczynki model, or otherwise as the reduced form estimates of a more general relationship between relative factor endowments and specialization.

In 7 sectors there is a negative and significant coefficient on the capital-labor ratio and in one sector there is a positive and significant coefficient. Most of the negative and significant coefficients are in the sectors with the lowest capital-labor ratios (e.g. *Textiles*, *Apparel*, *Rubber products*, and *Plastic products*). The positive and significant coefficient is in *Non-ferrous metals*, one of the sectors with a high capital-labor ratio. There are fewer significantly negative coefficients on capital in Table 7, but the sign pattern of the coefficients, significant or not, is broadly similar. As regards the skilled share, in Table 8, there are 9 sectors with positive and significant coefficients and two sectors with negative and significant coefficients. On the whole, the signs of the coefficients on the skilled share are more consistent with the evidence on factor intensites than are the coefficients on capital per worker. Sectors with significantly positive coefficients include most of the sectors with the highest observed skilled labor share (e.g., *Printing and publishing*, the chemical sectors, and the machinery sectors). The sectors with significantly negative coefficients are *Leather products* and *Footwear*, two of the sectors with the lowest skilled-labor intensities. Again, the broad pattern of signs is very similar in Table 7. In the case of the arable-labor ratio, the sign pattern is not robust across the two specifications, but for no sector is the estimated coefficient significantly different from zero. When we use gross output instead of value added, the results are almost unchanged. Additionally, we are concerned that a few less developed countries (mainly Turkey) may be driving the results. However, when we exclude it from the sample, there is no noticeable change, except for a loss of precision on average.[11]

Harrigan (1997) and Harrigan and Zakrajšek (2000) investigate the effect of factor endowments on specialization by estimating translog approximations to the revenue function. This framework allows for productivity differences, is immune to scale effects, and does not suffer from linear dependence of the regressors. As an approximation to the relationship between factor endowments and specialization, this framework is an alternative to the one we use in this section. We now compare the results to assess their robustness to the choice of specification of the relationship between factor endowments and specialization. Since Harrigan (1997) uses different factors of production from ours, we focus here on Harrigan and Zakrajšek (2000). The results are consistent in one crucial respect: They do not find a systematically positive and statistically significant impact of increasing capital abundance on output shares for manufacturing sectors. Harrigan and Zakrajšek also find that human and physical capital abundance raises output in machinery sectors, while physical capital lowers output in food and apparel-textiles. For smaller, more resource-based sectors, they have little success in explaining variation in output. These results are partially consistent with ours. We also find, as one of the strongest regularities across our specifications, that human capital raises significantly the share of output in the machinery sectors. But in contrast, we find that an increase in the capital-labor ratio reduces the share of output in these sectors, although the estimated coefficients are never significant. In *Food*, *Textiles* and *Apparel*, our results also indicate that an increase in the capital-labor ratio reduces the share of output (in *Textiles* and *Apparel* with a statistically significant effect). Lastly, our model also has difficulty in estimating precisely the effect of different factor proportions on smaller, more resource-based sectors like *Wood* and *Glass products*. However, there is one important difference between our strategy and that of Harrigan and Zakrajšek. They estimate using panel data with fixed and random effects. As a result, their identification comes mostly from across-time within-country variation, whereas our identification comes from cross-country

[11] Excluding the three countries with lowest GDP per capita also has no effect on the results.

variation at a single point in time. In the next section we explore what drives the identification in our model, and we suggest some reasons why such different identification strategies might or might not arrive at similar results.

5 Specialization and development

In this section we show that in our sample, relative factor endowments and the pattern of specialization are both strongly correlated with level of development. In fact, differences in the level of development are the main source of identification in our cross-section data. This raises the possibility that forces other than Heckscher-Ohlin can explain the results. Using our data, we cannot reject the possibility that these alternative forces drive the observed correlation between relative factor abundance and specialization. But additional evidence suggests that the Heckscher-Ohlin mechanism is still the driving force. Finally, we show that the factor proportions model can do a good job of predicting differences in the pattern of specialization between rich and poor OECD countries.

5.1 Factors and development

As we mentioned when discussing the productivity bias, the growth literature both predicts and finds a systematic relationship between relative factor endowments and per capita income. This is true for our sample of OECD countries. Figures 1, 2, 3 and 4 are scatter-plots of TFP and the three measures of factor abundance against GDP per capita. Table 9 gives the same information. This evidence is consistent with OECD countries being at different points along similar paths of development. As GDP per capita rises, the capital-labor ratio rises, the share of skilled labor in total labor rises and TFP also increases. We do not take a stand on the causal links between these variables. But we note some profound implications for the interpretation of our results that arise from their commovement. First, our independent variables are not linearly dependent, but there is nevertheless a systematic relationship between them. In particular, K/L and S/L have a correlation of 0.74 (Table 10 shows the full matrix of correlations between factor proportions). Given this correlation and the small sample size, we cannot always identify with precision the independent effect of changes in

K/L and changes in S/L on the pattern of specialization. What we identify is the common effect of moving along a similar path of development. This explains the paucity of significant coefficients in Table 8. In fact, it turns out that the variation in relative factor endowments that is correlated with differences across countries in level of development is the main source of identification for almost all sectors. This is clearly seen by including GDP per capita as an independent variable in the reduced form specification:

$$\frac{y_j^c}{Y^c} = \beta_{jU}^c + \beta_{jK}\frac{K^c}{L^c} + \beta_{jA}\frac{A^c}{L^c} + \beta_{jS}\frac{S^c}{L^c} + \frac{Y^c}{POP^c}\epsilon_j^c \tag{14}$$

In Table 11 we report the F-statistics and p-values for the joint restriction that the estimated coefficients on K/L, S/L and A/L are all zero. In only 5 sectors can we reject the restriction at the 10% level or lower. On the other hand, in only two sectors does GDP per capita add explanatory power after relative factor endowments have been controlled for. This means that it is hard to say whether specialization and relative factor endowments are each independently driven by level of development, or whether relative factor endowments are driven by level of development, and in turn drive the pattern of specialization.

5.2 Sources of identification

The fact that differences across countries in levels of development is the main source of econometric identification calls into question the extent to which a model such as we have estimated can be used as evidence either for or against Heckscher-Ohlin. Any model in which both factor accumulation and specialization are systematically related to development will generate a similar reduced form. For example, suppose that as countries become richer, TFP increases and physical and human capital accumulate. Suppose also that there are inter-sectoral non-homotheticicities in consumption [e.g. as in Hunter and Markusen (1988)]. Then more developed (i.e. richer) countries will have higher expenditure shares in some sectors than low-income countries, and vice versa. If countries trade very little relative to their total consumption (e.g. because of trade costs), production structure will be correlated with consumption patterns. In such a world, we would observe a correlation between patterns of specialization and relative factor endowments, even without any Heckscher-Ohlin mechanism at work. The relationship is not causal in either direction. It is other phenomena associated with the process of development that drive both relative factor abundance and production structure. An alternative model based on Ricardian differences generates a similar correlation. Suppose that richer countries are on average more productive than poorer countries, but that the productivity differential is higher in some sectors than in others. Then richer countries will have a comparative advantage (driven by Ricardian differences) in the sectors with the highest productivity differentials. Since richer countries are also capital and skilled-labor abundant, there will be a systematic correlation between factor endowments and specialization that is not due to Heckscher-Ohlin mechanisms.

Using data on sectoral output and endowments alone, we cannot distinguish between the different possible mechanisms driving specialization. Non-homotheticities in consumption, Ricardian differences and Heckscher-Ohlin could all generate the correlations between factor proportions and specialization that we observe. But for each mechanism there are additional predictions that can be checked using other data. For the Heckscher-Ohlin mechanism, this check is strongly supportive. Our estimates indicate for each sector and factor proportion the direction in which relative abundance should affect relative output. These estimates should be consistent with evidence on factor intensities in different sectors. We show that they are. This is strong support for the H-O theory of specialization. For the consumption non-homotheticity story, the evidence is less definitive. For non-homotheticities to explain our findings, sectors with high income elasticities (i.e. above 1) should be exactly those where countries with higher capital-labor ratios and skilled shares produce more. Hunter and Markusen (1988) find that the Food sector has an income elasticity lower than one, which is consistent with the observed and predicted lower shares of Food for richer countries. However, they find that the income elasticity is higher than one in many of our "low development" sectors, where the sectoral share of production decreases as a country grows (Beverages, Tobacco, Clothing, and Footwear). Lastly, if the Ricardian mechanism is important, then we should find that productivity differences between rich and poor countries are indeed larger for "high development" sectors than for "low development" sectors. Harrigan (1997) calculates relative TFP for 10 OECD countries in different manufacturing sectors. This evidence does not clearly support a Ricardian explanation for our results.

It is appropriate at this point to address the similarity between our results and those of Harrigan and Zakrajšek (2000). While our identification comes from cross-section variation, theirs comes from time-series variation. They observe countries over a period of 20 years during which relative factor endowments change because there is accumulation of physical and human capital. If all countries accumulate factors at the same rate, the factor proportions of any one country relative to the others will not change much and we would not expect H-O mechanisms to drive changes in specialization.[12] However, if Heckscher-Ohlin mechanisms are indeed what drives specialization, and if countries accumulate factors at different rates, we would expect the effect of relative factor abundance on specialization to be identified. This may indeed be what drives their coefficient estimates, especially if, as some evidence shows, the growth process is non-linear. But it is also possible, as in the cross-section, that either of the two alternative mechanisms we have described is at work. Moreover, in a time-series context, new alternatives arise. For example, Harrigan and Zakrajšek assume that cross-country differences in relative prices are constant over time. However, the period 1970-1990 is one of substantial trade liberalization, inducing movements in relative prices that may be quite different across countries. In a sample driven mostly by OECD countries, we would observe shifts over time out of "low-development" sectors and into "high-development" sectors as a result of liberalization. This would not be causally linked to the changes in within-country factor abundance, but would still be correlated with them in the time dimension. In sum, the similar cross-section and time-series results may be driven by the same H-O mechanisms, but additional research (both theoretical and empirical) is needed to confirm that they are.

5.3 Prediction

We believe that there are Heckscher-Ohlin mechanisms at work in driving the correlation between specialization and relative factor endowments. In the light of the alternative hypotheses we have outlined, we are unable to prove this using our data set and estimating equation. We point to some types of external evidence that could better decide the question. So far the evidence is suggestive, but it is not conclusive. We see these other avenues as

[12] We abstract here from the general equilibrium effects of the world accumulation of factors on goods and factor prices, factor intensities, etc.

fruitful for future research on the Heckscher-Ohlin link between endowments and specialization. In this section, we try to answer the question: "How does the pattern of specialization change as countries develop and accumulate physical and human capital, and how much of this change can be attributed to the implied changes in factor proportions?".

To explore the effect of development on specialization, we perform the following exercise. We rank our sample of countries by GDP per capita, and select the bottom quartile (Turkey, Portugal, Greece, Spain, and Ireland) and the top quartile (Japan, Norway, Sweden, Finland, and the US). For each of these two groups, we calculate the group average of the three factor abundance ratios. For the resulting two synthetic countries, "poor" and "rich", we use the estimated model (13) to predict the expected share of GDP in each manufacturing sector. We can then predict how the pattern of manufacturing specialization would change if a "poor" country were to grow and become "rich". The results are shown in Table 12. The first two columns of the table show the average of the observed sectoral shares of GDP for the two groups of countries. Column 3 shows the observed difference. Poor countries have larger GDP shares than rich countires in 13 sectors and smaller GDP shares than rich countries in 12 sectors. On average, sectors that grow as countries become richer double as a share of GDP and sectors that shrink as countries become richer shrink by half. Column 4 gives the prediction of the model for the expected difference in the shares and column 5 the standard error of this prediction. The sign of the predicted change matches the sign of the actual change in all sectors except one. The predicted change is significantly different from zero (at the 10% level) in 16 of the 25 sectors. Focusing on these sectors, the model predicts that as a "poor" country becomes "rich" – within the development range of these countries – it shifts production towards *Wood*, *Furniture*, *Paper and publishing*, *Plastic products*, *Non-ferrous metals*, *Fabricated metal products*, *Electrical machinery*, *Non-electrical Machinery* and *Transport equipment*. On the other hand, it shifts production away from *Textiles*, *Apparel*, *Leather products*, *Footwear*, *Glass*, and *Other non-metallic mineral products*. The last three columns of the table examine how well the observed reallocation is predicted by the factor proportions model. Column 6 gives the absolute value of column 3. The sum of the entries in column 6 is the implied inter-sectoral reallocation in manufacturing if a "poor" country grows and becomes "rich". Of the observed inter-sectoral reallocation (13.44 percent of GDP), the model explains 8.83 percentage points. Prediction error accounts for the remaining 4.61 percentage points. That is, the model is able to explain two thirds (66%) of the observed difference in sectoral allocation between the poor and rich quartiles. These results suggest that differences in what countries produce are strongly correlated with differences in their factor proportions even within OECD countries. This is in spite of the fact that differences in factor proportions and output specialization in the OECD are small compared with those in broader samples of countries.

6 Conclusion

This paper attempts to answer an old question: How do relative factor endomwents affect specialization? In the trade literature, in contrast to the growth literature, relative factor endowments are usually taken as given. But they are the outcome of an accumulation process. We explicitly take this endogeneity into account. This affects both our choice of empirical specification and our interpretation of the results. We first show that the results of an important part of the empirical literature are biased by the failure to control for productivity differences across countries. The bias arises because productivity affects factor accumulation, and hence differences in productivity are correlated with differences in factor endowments. We adjust the classic Rybczynki framework to take account of productivity differences. This eliminates the productivity bias. We further transform this specification to arrive at an estimating equation that is a reduced-form approximation to a more general relationship between specialization and relative factor endowments. We show that the identification of this empirical model comes through cross-country differences in levels of development. Since factor proportions are systematically related through the development process, we cannot always identify with precision the separate effects of individual factor ratios on specialization. In consequence, regressions of specialization on relative factor endowments are unable to distinguish between the Heckscher-Ohlin model of specialization and some other plausible alternatives that we outline. However, our significant coefficients are consistent with evidence on factor intensities across sectors. The factor proportions model also does a good job of predicting the pattern of specialization. In particular, it predicts 2/3 of the actual difference in manufacturing specialization between poor and rich OECD countries.

References

[1] Ball, V. E., J.-C. Bureau, J.-P. Butault and R. Nehring (1999), "Levels of Farm Sector Productivity: An International Comparison," USDA, mimeo.

[2] Bernstein, J. and D. Weinstein (2002), "Do Endowments Predict the Location of Production? Evidence From National and International Data," *Journal of International Economics*, 56 (1), pp. 55-76.

[3] Conrad, K and D. Jorgenson (1995), "Sectoral Productivity Gaps Between the United States, Japan and Germany, 1960-1979," in D. Jorgenson, ed., *Productivity: International Comparisons of Economic Growth*, (Cambridge MA: MIT Press).

[4] Davis, D. and D. Weinstein (1998), "Does Economic Geography Matter for International Specialization?" Harvard University, mimeo.

[5] Davis, D. and D. Weinstein (2001), "An Account of Global Factor Trade," *American Economics Review*, 91 (5), pp. 1423-1453.

[6] Davis, D., D. Weinstein, S. Bradford and K. Schimpo (1997), "Using International and Japanese Regional Data to Determine When the Factor Abundance Theory of Trade Works," *American Economic Review*, 87 (3), pp. 421-446.

[7] Deardorff, A. (1982), "The General Validity of the Heckscher-Ohlin Theorem," *American Economic Review*, 72 (4), pp. 683-694.

[8] Dougherty, C. and D. Jorgenson (1996), "International Comparisons of the Sources of Economic Growth," *American Economic Review*, 86 (2), pp. 25-29.

[9] Hall, R. and C. Jones (1999), "Why Do Some Countries Produce so Much More Output per Worker than Others?" *Quarterly Journal of Economics*, 114 (1), pp. 83-116.

[10] Harrigan, J (1993), "OECD Imports and Trade Barriers in 1983," *Journal of International Economics*, 35, pp. 91-111.

[11] Harrigan, J. (1995), "Factor Endowments and the International Location of Production: Econometric Evidence from the OECD, 1970-1985," *Journal of International Economics*, 39 (1/2), pp. 123-141.

[12] Harrigan, J. (1997), "Technology, Factor Supplies and International Specialization: Testing the Neoclassical Model," *American Economic Review*, 87 (4), pp. 475-494.

[13] Harrigan, J. and E. Zakrajšek (2000), "Factor Supplies and Specialization in the World Economy," NBER Working Paper 7848.

[14] Harrigan, J. (2002), "Specialization and the Volume of Trade: Do the Data Obey the Laws?," NBER Working Paper 8675.

[15] Hunter, L. and J. Markusen (1988), "Per-Capita Income as a Determinant of Trade, in R. Feenstra, ed., *Empirical Methods for International Trade*, (Cambridge, MA, MIT Press).

[16] Islam, N. (1995), "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics*, 110 (4), pp. 1127-1170.

[17] Islam, N. (1999), "International Comparison of Total Factor Productivity: A Review," Review of Income and Wealth, 45 (4), pp. 493-518.

[18] Klenow, P. and A. Rodriguez-Clare (1997), "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" in B. Bernanke and J. Rotemberg eds., *NBER Macroeconomics Annual 1997* (Cambridge MA: MIT Press).

[19] Leamer, E. (1984), *Sources of International Comparative Advantage*, (Cambridge MA, and London: The MIT Press).

[20] Leamer, E. (1987), "Paths of Development in the Three-Factor, n-Good General Equilibrium Model," *Journal of Political Economy*, 95 (5), pp. 961-999.

[21] Reeve, T. (1998), "Explaining Industrial Structure," Harvard University, mimeo.

[22] Romalis, J. (2002), "Factor Proportions and the Structure of Commodity Trade", Chicago GSB, mimeo.

[23] Schott, P. (1999), "One Size Fits All? Theory, Evidence and Implications of Cones of Diversification," UCLA, mimeo.

[24] Trefler, D. (1993), "International Factor Price Differences: Leontief Was Right!," *Journal of Political Economy*, 101 (6), pp. 961-987.

[25] Trefler, D. (1995), "The Case of the Missing Trade and Other Mysteries," *American Economic Review*, 85 (5), pp. 1029-1046.

A Appendix: Data sources and construction

A.1 Endowments

The capital stock in 1988 comes from the PWT. It is measured in million dollars. It is composed of three different types of capital: producer durables, non-residential construction, and residential construction. Each category of capital is constructed using the perpetual inventory method with investment flows converted to US dollars by the relevant PPP. A different depreciation rate is used for different categories: 3.5% for all types of construction, 15% for machinery and 24% for transport equipment. We use non-residential capital as our measure of the capital stock. It is the sum of producer durables and nonresidential construction. Capital stock measures in the PWT are obtained by converting investment series into dollars using investment PPPs. This is the appropriate conversion to obtain comparable measures of capital in "physical" units.

The labor force in 1988 also comes from the PWT. It is measured in thousands. To obtain skilled and unskilled labor, we use data on educational attainment from the OECD publication *Education at a Glance* (1992 and 1993). The standard in the literature is to use the Barro-Lee data set. We believe that for OECD countries, the OECD education data are more reliable.[13] For most countries, the data refer to 1989, but for some they refer to 1987, 1988 or 1990. We define as skilled all those workers who have at least some upper-cycle second level education or higher. We define as unskilled all those who do not have upper-cycle second level. We combine information on educational attainment of the total population aged 25-64 (Table C.1 in *Education at a Glance)* with information on labor force participation rates by educational attainment (Table C.5) to obtain percentages of the labor force in each category.

The stock of arable land in 1988 is from the FAO *Statistical Yearbook* (FAO). It is measured in thousand hectares.

[13]The Barro-Lee estimates do not count vocational education and apprenticeships as education. As a result, they underestimate the educational attainment of several European countries.

A.2 Output

Sectoral output data (gross output and value added) for 1988 come from the UNIDO Industrial Demand-Supply Balance Database, 3-digit ISIC Codes. We exclude three sectors from our sample. One is a residual category. The other two are *Petroleum refineries* and *Miscellaneous petroleum and coal products*. We exclude them first, because many countries do not report data on these sectors. Second, some countries report output to UNIDO at producer prices, while others report it at factor value. Tax differences in these sectors are big, and they can lead to large distortions in cross-country comparisons of output figures. GDP data come from OECD National Accounts - Detailed Tables, 1983-1995 (OECD-DT). To get GDP at factor cost, we sum Consumption of fixed capital, Compensation of employees paid by resident producers, and Operating surplus (Table 1). For consistency with excluding residential construction from the capital stock, we additionally subtract Gross rent (GR) from GDP (line 9, Table 2). This component represents on average 11% of GDP. Three countries do not report data on GR, but on a slightly more aggregated item, Gross Rent, Fuel, and Power (GRFP). For them, we impute the ratio of GR to GRFP in the other countries. For Turkey (which reports neither GR nor GRFP), we use the average ratio of GR to GDP for all other countries to impute GR. We call this measure Adjusted GDP (AGDP). This is the measure of GDP we use in the paper.

All output measures are converted to thousand US dollars using the average yearly market exchange rate for 1988 from International Financial Statistics (IFS). This conversion implicitly assumes that the law of one price holds for manufacturing output (already assumed for FPE). In converting this way, we follow the convention in the trade literature.

A.3 Factor prices and factor intensities

To construct our productivity indices, we need data on factor prices. The details of construction are given in Appendix B. Here, we describe the data sources. We take the functional distribution of income from OECD-DT. We take the share of self-employed in the labor force from the *Yearbook of Labor Statistics* (ILO). We estimate the ratio of skilled to unskilled wages for the US from the Integrated Public Use Microdata Series (IPUMS) for 1990. This is a 1% sample of the 1990 US Population Census. From Ball et al. (1999), we obtain data on the total value of arable land in the US, and its rental price in 1988. Data to estimate income to land in all other countries come from OECD-DT

Factor intensities by sector are for the US. The capital stock for each sector is calculated from UNIDO current-price data on sectoral gross fixed capital formation (deflated by the deflator for total gross fixed capital formation in the US) using the perpetual inventory method with rate of depreciation 10% per annum. The initial year used is 1963 and the final year used is 1987. Labor force is employment in each sector in 1988, also from UNIDO. Capital-labor ratios are expressed relative to the average capital-labor ratio across all included sectors. So in Table 4, a value of 0.82 in the *Food products* sector means that the capital-labor ratio in *Food products* is 82% of the average capital-labor ratio across manufacturing sectors. Skilled and unskilled share are derived using the 1988 March CPS. Employed workers are assigned to 3-digit ISIC sectors according to the industry they work in (correspondence available on request). Those employed in a particular sector who are not high school graduates are considered unskilled. Those with high school diplomas or more education are considered skilled.

B Appendix: Productivity estimates

We calculate productivity levels as in (10). To do this, we require data on factor prices for the numeraire country, the US. From OECD-DT, we divide AGDP into the compensation of employees and a residual. We must then divide the compensation of employees into the compensation of skilled labor and the compensation of unskilled labor. We do this by taking the ratio of average skilled wages to average unskilled wages. This ratio is 1.63. So if w_u is the compensation of unskilled, and w_s is the compensation of skilled workers, we will have

$$\begin{aligned} w_u U + w_s S &= \text{Total compensation of labor} \\ w_u U + 1.63\,(w_u)\,S &= \text{Total compensation of labor} \end{aligned}$$

From this we can back out w_u and hence w_s.

We must divide the residual of AGDP into the compensation of capital and the compensation of land. From Ball (1999) we take the total compensation of land. Dividing this by the stock of land, we obtain the return to land, w_l. We subtract the total compensation of land from the residual of AGDP to get the total compensation of capital. We divide this by the stock of non-residential capital to obtain the return to capital, w_k. The factor prices we get for the US in 1988 are:

$$\begin{aligned}
w_u &= 15877 \text{ \$ per person} \\
w_s &= 25951 \text{ \$ per person} \\
w_l &= 153 \text{ \$ per hectare} \\
w_k &= 0.266 \text{ \$ per \$ of capital stock, inclusive of depreciation}
\end{aligned}$$

Table 1. Summary statistics of output data

Sector	Description	Average share[a]	Coeff. of variation
311	Food products	2.97	0.52
313	Beverages	0.72	0.52
314	Tobacco	0.41	0.90
321	Textiles	1.09	0.64
322	Wearing apparel	0.53	0.40
323	Leather products	0.08	0.66
324	Footwear	0.14	0.81
331	Wood products	0.61	0.62
332	Furniture, exc. Metal	0.42	0.55
341	Paper and products	1.19	0.84
342	Printing and publishing	1.38	0.44
351	Industrial chemicals	1.59	0.53
352	Other chemicals	1.31	0.62
355	Rubber products	0.28	0.47
356	Plastic products	0.63	0.47
361	Pottery, china, earth.	0.13	0.84
362	Glass and products	0.26	0.48
369	Other non-met.min.pr.	0.90	0.33
371	Iron and steel	1.06	0.54
372	Non-ferrous metals	0.55	0.67
381	Fabricated metal prod.	1.59	0.38
382	Machinery, exc. elect.	2.63	0.65
383	Machinery electric	2.29	0.68
384	Transport equipment	2.20	0.64
385	Prof. & scient. equip.	0.42	1.15

[a] Sectoral value added as a share of GDP

Table 2. Factor Abundance
The endowments paradox

Country	Capital	Skilled	Unskilled	Land
AUS	1.288	1.028	1.249	6.752
AUT	1.108	1.093	0.880	0.426
BEL	1.068	0.646	1.564	0.179
CAN	1.238	1.104	0.672	3.496
DEN	1.081	0.935	1.199	0.945
FIN	1.221	0.815	1.010	0.864
FRA	1.082	0.814	1.321	0.699
GER	1.071	1.038	0.437	0.364
GRE	1.512	1.118	3.857	1.526
IRE	0.949	0.871	2.364	0.976
ITA	0.918	0.458	1.937	0.368
JAP	0.986	1.016	0.708	0.051
NET	0.940	0.865	1.036	0.134
NZE	1.394	1.154	1.553	2.268
NOR	1.206	0.811	0.723	0.331
POR	1.095	0.467	9.258	1.728
SPA	1.097	0.548	3.144	1.567
SWE	0.962	0.820	0.782	0.546
TUR	2.193	2.599	22.061	9.577
UK	0.810	1.311	1.201	0.320
USA	0.932	1.089	0.377	1.353
Coef. of variation	0.254	0.444	1.769	1.440

Note: Factor abundance is calculated as: $(v_f^c/Y^c) / (v_f^w/Y^w)$

Table 3. Unadjusted Rybczynski equations

Sector	Capital	t		Skilled	t		Unskilled	t		Arable	t		N	APE
Food products	22.16	1.92	*	0.363	0.59		-0.130	1.17		-44.2	0.57		21	0.36
Beverages	5.14	1.83	*	0.089	0.60		-0.018	0.68		-13.3	0.70		21	0.37
Tobacco	-0.81	0.41		0.232	2.21	**	0.027	1.40		-19.1	1.43		21	0.82
Textiles	10.12	3.35	***	-0.135	0.84		0.119	4.09	***	-35.9	1.76	*	21	0.52
Wearing apparel	4.97	3.29	***	-0.025	0.32		0.002	0.16		-4.4	0.43		21	0.67
Leather products	1.48	4.07	***	-0.038	2.02	*	0.002	0.45		-2.3	0.95		20	0.84
Footwear	2.74	3.85	***	-0.085	2.28	**	0.008	1.20		-5.1	1.09		20	1.27
Wood products	7.00	2.89	**	-0.057	0.44		-0.054	2.31	**	9.1	0.56		21	0.60
Furniture, exc. Metal	3.19	2.17	**	0.075	0.96		-0.032	2.30	**	-9.4	0.95		21	0.55
Paper and products	13.33	1.93	*	-0.054	0.15		-0.071	1.06		-15.6	0.33		21	0.74
Printing and publishing	6.90	1.80	*	0.412	2.02	*	-0.127	3.44	***	-13.6	0.53		21	0.47
Industrial chemicals	6.26	1.07		0.513	1.65		0.015	0.26		-82.7	2.10	*	21	0.52
Other chemicals	2.77	0.47		0.559	1.78	*	-0.041	0.73		-47.5	1.20		21	0.54
Rubber products	0.97	1.01		0.088	1.73		-0.002	0.21		-7.7	1.20		21	0.56
Plastic products	2.24	1.09		0.232	2.16	**	-0.044	2.31	**	-13.9	1.03		20	0.47
Pottery, china, earth.	1.25	2.13	*	-0.016	0.53		0.020	3.61	***	-9.3	2.41	**	19	0.65
Glass and products	1.22	1.27		0.059	1.17		0.007	0.81		-9.5	1.50		20	0.57
Other non-met.min.pr.	5.93	2.45	**	0.133	1.05		0.002	0.11		-28.9	1.81	*	20	0.35
Iron and steel	3.03	0.80		0.369	1.83	*	0.000	0.00		-32.3	1.25		20	0.73
Non-ferrous metals	5.42	2.62	**	-0.023	0.20		-0.056	2.83	**	21.7	1.54		20	1.14
Fabricated metal prod.	8.76	2.21	**	0.434	2.10	*	-0.108	2.91	**	-35.2	1.35		20	0.31
Machinery, exc. elect.	4.90	0.44		1.359	2.37	**	-0.139	1.35		-147.2	2.03	*	20	0.95
Machinery electric	2.58	0.26		1.270	2.45	**	-0.081	0.88		-149.3	2.28	**	20	0.69
Transport equipment	6.84	0.67		0.851	1.59		-0.152	1.59		-46.4	0.69		20	0.82
Prof. & scient. equip.	-1.24	0.38		0.316	1.85	*	-0.036	1.17		-17.6	0.81		20	2.05
													Average:	0.70

Note: The coefficients on Capital and Arable land are scaled by a factor of 1000.

Table 4. Factor intensities by sector

Sector	Unskilled share[a]	Skilled share[a]	K/L ratio[b]
Food products	28	72	0.82
Beverages	17	83	1.96
Tobacco	28	72	2.41
Textiles	40	60	0.51
Wearing apparel	47	53	0.12
Leather products	35	65	0.28
Footwear	41	59	0.19
Wood products	36	64	0.56
Furniture, exc. Metal	34	66	0.25
Paper and products	20	80	1.89
Printing and publishing	18	82	0.50
Industrial chemicals	8	92	3.51
Other chemicals	9	91	1.16
Rubber products	24	76	0.77
Plastic products	26	74	0.62
Pottery, china, earth.	39	61	0.40
Glass and products	21	79	1.12
Other non-met.min.pr.	25	75	1.02
Iron and steel	27	73	1.69
Non-ferrous metals	25	75	1.37
Fabricated metal prod.	24	76	0.53
Machinery, exc. elect.	14	86	0.75
Machinery electric	17	83	0.93
Transport equipment	18	82	0.97
Prof. & scient. equip.	12	88	0.47

[a] Shares of total employment in the sector.

[b] Expressed relative to the average K/L ratio across manufacturing sectors.

Table 5. Hicks-neutral TFP and Adjusted Factor Abundance

Country	HN-TFP	Capital	Skilled	Unskilled	Land
AUS	0.80	1.082	0.868	1.216	6.108
AUT	0.88	1.019	1.011	0.939	0.422
BEL	1.03	1.151	0.700	1.955	0.208
CAN	0.86	1.117	1.001	0.703	3.398
DEN	0.92	1.036	0.901	1.333	0.976
FIN	0.98	1.249	0.837	1.198	0.952
FRA	0.97	1.090	0.825	1.544	0.759
GER	0.99	1.104	1.076	0.522	0.405
GRE	0.56	0.881	0.655	2.608	0.958
IRE	0.82	0.813	0.751	2.350	0.901
ITA	1.14	1.092	0.547	2.671	0.472
JAP	0.98	1.008	1.044	0.839	0.056
NET	1.03	1.007	0.932	1.289	0.155
NZE	0.72	1.055	0.878	1.363	1.848
NOR	1.04	1.310	0.885	0.911	0.387
POR	0.45	0.513	0.220	5.038	0.873
SPA	0.83	0.953	0.479	3.168	1.467
SWE	1.10	1.103	0.945	1.040	0.675
TUR	0.16	0.374	0.445	4.361	1.758
UK	0.81	0.681	1.109	1.172	0.290
USA	1.00	0.974	1.143	0.456	1.522
Coef. of variation	0.270	0.230	0.293	0.702	1.166
Correlation with HN-TFP		0.833	0.559	-0.714	-0.252

Note: Factor abundance is calculated as: $(a^c v_f^c / Y^c) / (\Sigma_c a^c v_f^c / Y^w)$

Table 6. Productivity-adjusted Rybczynski equations

Sector	Capital	t	Skilled	t	Unskilled	t	Arable	t	N	APE
Food products	-2.30	0.14	1.269	1.65	0.480	1.73	23.9	0.27	21	0.34
Beverages	-2.12	0.55	0.353	1.92 *	0.160	2.41 **	5.6	0.26	21	0.35
Tobacco	-5.58	1.62	0.417	2.52 **	0.148	2.47 **	-12.9	0.68	21	0.86
Textiles	-9.35	2.80 **	0.544	3.39 ***	0.631	10.92 ***	0.9	0.05	21	0.31
Wearing apparel	-1.69	0.94	0.210	2.43 **	0.166	5.35 ***	13.5	1.35	21	0.56
Leather products	0.70	1.31	-0.013	0.53	0.026	2.95 ***	-0.2	0.09	20	0.78
Footwear	0.73	0.76	-0.016	0.36	0.060	3.77 ***	-0.3	0.06	20	1.11
Wood products	4.92	1.40	0.039	0.23	-0.023	0.37	24.6	1.26	21	0.58
Furniture, exc. Metal	2.39	1.14	0.115	1.14	-0.010	0.26	-4.4	0.38	21	0.51
Paper and products	10.45	1.03	0.101	0.21	-0.030	0.17	7.8	0.14	21	0.70
Printing and publishing	-0.54	0.11	0.752	3.32 ***	-0.007	0.09	15.2	0.58	21	0.40
Industrial chemicals	-5.15	0.66	0.992	2.64 **	0.317	2.35 **	-68.9	1.59	21	0.43
Other chemicals	-13.17	1.77 *	1.203	3.38 ***	0.275	2.14 **	-15.1	0.37	21	0.36
Rubber products	-1.80	1.43	0.196	3.26 ***	0.066	3.04 ***	-1.9	0.28	21	0.44
Plastic products	-3.01	1.18	0.458	3.80 ***	0.044	1.05	-0.7	0.05	20	0.37
Pottery, china, earth.	-0.77	1.11	0.053	1.63	0.081	7.27 ***	-6.7	1.83 *	19	0.49
Glass and products	-1.97	1.68	0.178	3.23 ***	0.087	4.53 ***	-3.6	0.57	20	0.42
Other non-met.min.pr.	-3.99	1.43	0.501	3.81 ***	0.239	5.21 ***	-6.7	0.45	20	0.28
Iron and steel	-2.53	0.44	0.602	2.17 **	0.184	1.85 *	-24.6	0.76	20	0.74
Non-ferrous metals	5.44	1.70	-0.019	0.12	-0.044	0.79	32.6	1.82 *	20	1.20
Fabricated metal prod.	1.17	0.24	0.795	3.52 ***	0.025	0.32	-11.9	0.47	20	0.25
Machinery, exc. elect.	-6.86	0.46	1.950	2.75 **	0.095	0.39	-130.5	1.62	20	0.69
Machinery electric	-14.38	1.09	2.064	3.32 ***	0.214	0.99	-131.5	1.87 *	20	0.54
Transport equipment	-6.26	0.45	1.481	2.28 **	0.055	0.24	-8.8	0.12	20	0.70
Prof. & scient. equip.	-5.80	1.25	0.528	2.41 **	0.017	0.22	-7.6	0.31	20	1.71
									Average:	0.60

Note: The coefficients on Capital and Arable land are scaled by a factor of 1000.

Table 7. Transformed productivity-adjusted Rybczynski equations

Sector	K/L	t		S/L	t		A/L	t		Constant	t		N	R^2	APE
Food products	-4.16	0.27		0.602	0.86		30.1	0.40		0.632	1.90	*	21	0.07	0.35
Beverages	-2.28	0.62		0.163	0.98		5.7	0.32		0.181	2.29	**	21	0.06	0.36
Tobacco	-4.01	1.10		0.264	1.59		-18.1	1.03		0.110	1.40		21	0.17	0.92
Textiles	-9.34	2.76	**	-0.038	0.25		1.3	0.08		0.603	8.24	***	21	0.53	0.31
Wearing apparel	-2.40	1.22		0.064	0.72		15.1	1.58		0.174	4.10	***	21	0.18	0.55
Leather products	0.32	0.59		-0.029	1.17		0.2	0.09		0.031	2.71	**	20	0.09	0.73
Footwear	0.14	0.16		-0.054	1.39		1.3	0.32		0.063	3.57	***	20	0.19	1.06
Wood products	6.23	1.65		0.067	0.39		23.7	1.30		-0.063	0.77		21	0.40	0.59
Furniture, exc. Metal	2.00	0.89		0.131	1.27		-3.2	0.29		-0.003	0.05		21	0.34	0.52
Paper and products	14.23	1.26		0.141	0.27		7.7	0.14		-0.147	0.60		21	0.23	0.76
Printing and publishing	-0.06	0.01		0.716	3.12	***	18.0	0.74		0.000	0.00		21	0.57	0.40
Industrial chemicals	-4.42	0.52		0.695	1.80	*	-69.1	1.68		0.285	1.55		21	0.28	0.44
Other chemicals	-15.43	2.14	**	0.971	2.96	***	-12.2	0.35		0.314	2.02	*	21	0.34	0.36
Rubber products	-2.15	1.58		0.150	2.40	**	-2.4	0.36		0.066	2.24	**	21	0.26	0.43
Plastic products	-4.50	1.63		0.465	3.72	***	1.1	0.09		0.057	1.01		20	0.52	0.37
Pottery, china, earth.	-0.79	1.20		-0.024	0.80		-6.2	2.02	*	0.079	5.84	***	19	0.50	0.47
Glass and products	-2.09	1.74		0.099	1.81	*	-3.9	0.69		0.087	3.49	***	20	0.21	0.43
Other non-met.min.pr.	-4.29	1.46		0.253	1.89	*	-6.2	0.45		0.252	4.15	***	20	0.19	0.28
Iron and steel	-1.37	0.24		0.420	1.58		-28.6	1.00		0.154	1.23		20	0.23	0.73
Non-ferrous metals	7.62	2.14	**	-0.012	0.07		29.9	1.71		-0.085	1.10		20	0.48	1.19
Fabricated metal prod.	0.01	0.00		0.851	3.53	***	-13.0	0.52		0.014	0.13		20	0.64	0.25
Machinery, exc. elect.	-8.28	0.53		1.912	2.70	**	-130.9	1.78	*	0.105	0.33		20	0.48	0.70
Machinery electric	-18.25	1.28		2.035	3.13	***	-128.7	1.91	*	0.221	0.75		20	0.49	0.55
Transport equipment	-10.44	0.69		1.729	2.53	**	-7.8	0.11		0.006	0.02		20	0.38	0.70
Prof. & scient. equip.	-7.47	1.55		0.570	2.60	**	-6.2	0.28		0.031	0.31		20	0.31	1.78
													Average:	0.33	0.61

Note: The coefficients on K/L and A/L are scaled by a factor of 1000.

Table 8. Reduced form specification

Sector	K/L	t	S/L	t	A/L	t	Constant	t	N	R^2	APE
Food products	-0.386	0.68	13.34	0.52	0.713	0.26	32.9	2.69 **	21	0.03	0.34
Beverages	-0.149	1.11	3.35	0.55	0.153	0.23	9.6	3.31 ***	21	0.08	0.37
Tobacco	-0.205	1.65	7.29	1.29	-0.495	0.82	6.7	2.48 **	21	0.18	0.92
Textiles	-0.478	3.50 ***	-7.99	1.28	0.067	0.10	29.8	10.10 ***	21	0.73	0.33
Wearing apparel	-0.130	2.10 *	-0.40	0.14	0.433	1.44	9.0	6.75 ***	21	0.40	0.53
Leather products	0.007	0.40	-1.51	1.80 *	-0.001	0.01	1.5	3.84 ***	20	0.25	0.76
Footwear	-0.004	0.11	-2.87	1.83 *	0.019	0.11	3.1	4.33 ***	20	0.35	1.05
Wood products	0.150	1.25	0.76	0.14	0.693	1.20	0.4	0.15	21	0.27	0.56
Furniture, exc. Metal	0.048	0.64	3.30	0.96	-0.149	0.41	1.0	0.61	21	0.22	0.51
Paper and products	0.345	0.99	1.88	0.12	0.137	0.08	0.3	0.04	21	0.14	0.68
Printing and publishing	-0.103	0.60	21.68	2.79 **	0.411	0.50	4.1	1.12	21	0.44	0.39
Industrial chemicals	-0.302	1.09	17.73	1.41	-2.201	1.65	17.2	2.89 **	21	0.22	0.44
Other chemicals	-0.610	2.37 **	27.62	2.35 **	-0.463	0.37	16.3	2.92 ***	21	0.28	0.34
Rubber products	-0.094	2.17 **	3.69	1.86 *	-0.078	0.37	3.7	3.89 ***	21	0.23	0.42
Plastic products	-0.176	2.02 *	13.22	3.34 ***	-0.024	0.06	4.0	2.20 **	20	0.42	0.35
Pottery, china, earth.	-0.045	1.74	-1.66	1.42	-0.197	1.63	3.8	7.18 ***	19	0.64	0.51
Glass and products	-0.097	2.38 **	2.10	1.13	-0.121	0.63	4.5	5.29 ***	20	0.33	0.42
Other non-met.min.pr.	-0.234	2.42 **	5.27	1.20	-0.223	0.49	13.2	6.60 ***	20	0.33	0.27
Iron and steel	-0.154	0.76	10.49	1.13	-0.886	0.89	10.3	2.37 **	20	0.11	0.73
Non-ferrous metals	0.190	1.76 *	-1.12	0.23	0.910	1.73	-0.6	0.26	20	0.39	1.13
Fabricated metal prod.	-0.090	0.55	23.63	3.22 ***	-0.489	0.64	5.5	1.65	20	0.54	0.24
Machinery, exc. elect.	-0.443	0.84	57.52	2.40 **	-4.176	1.68	11.2	1.03	20	0.39	0.71
Machinery electric	-0.729	1.61	59.92	2.92 **	-4.115	1.93 *	14.9	1.59	20	0.44	0.53
Transport equipment	-0.434	0.93	48.12	2.27 **	-0.398	0.18	7.8	0.81	20	0.29	0.66
Prof. & scient. equip.	-0.254	1.58	17.37	2.39 **	-0.232	0.31	2.0	0.61	20	0.27	1.65
									Average:	0.32	0.59

Note: All coefficients are scaled by a factor of 1000.

Table 9. Relative Factor Abundance

Country	GDP[a] per cap.	K/L[b]	S/L[c]	A/L[d]
JAP	19806	32.46	0.75	0.05
NOR	18516	46.56	0.71	0.41
SWE	18383	36.00	0.69	0.66
FIN	16824	42.08	0.63	0.96
USA	16442	32.71	0.86	1.54
GER	15738	38.25	0.84	0.42
DEN	15607	32.05	0.62	0.91
CAN	14920	38.72	0.78	3.54
FRA	13448	33.49	0.57	0.70
AUT	13278	32.66	0.73	0.41
NET	12917	30.89	0.64	0.14
BEL	12754	34.37	0.47	0.19
ITA	12479	29.85	0.34	0.39
AUS	12428	35.43	0.64	6.01
UK	11119	19.17	0.70	0.24
NZE	10071	32.87	0.61	1.73
IRE	8197	21.28	0.44	0.71
SPA	7551	24.09	0.27	1.11
GRE	5532	22.94	0.38	0.75
POR	3954	10.11	0.10	0.52
TUR	1420	7.52	0.20	1.06

[a] US dollars.
[b] Thousand dollars per worker.
[c] Share in the labor force.
[d] Thousand hectares per worker.

Table 10. Matrix of Correlations

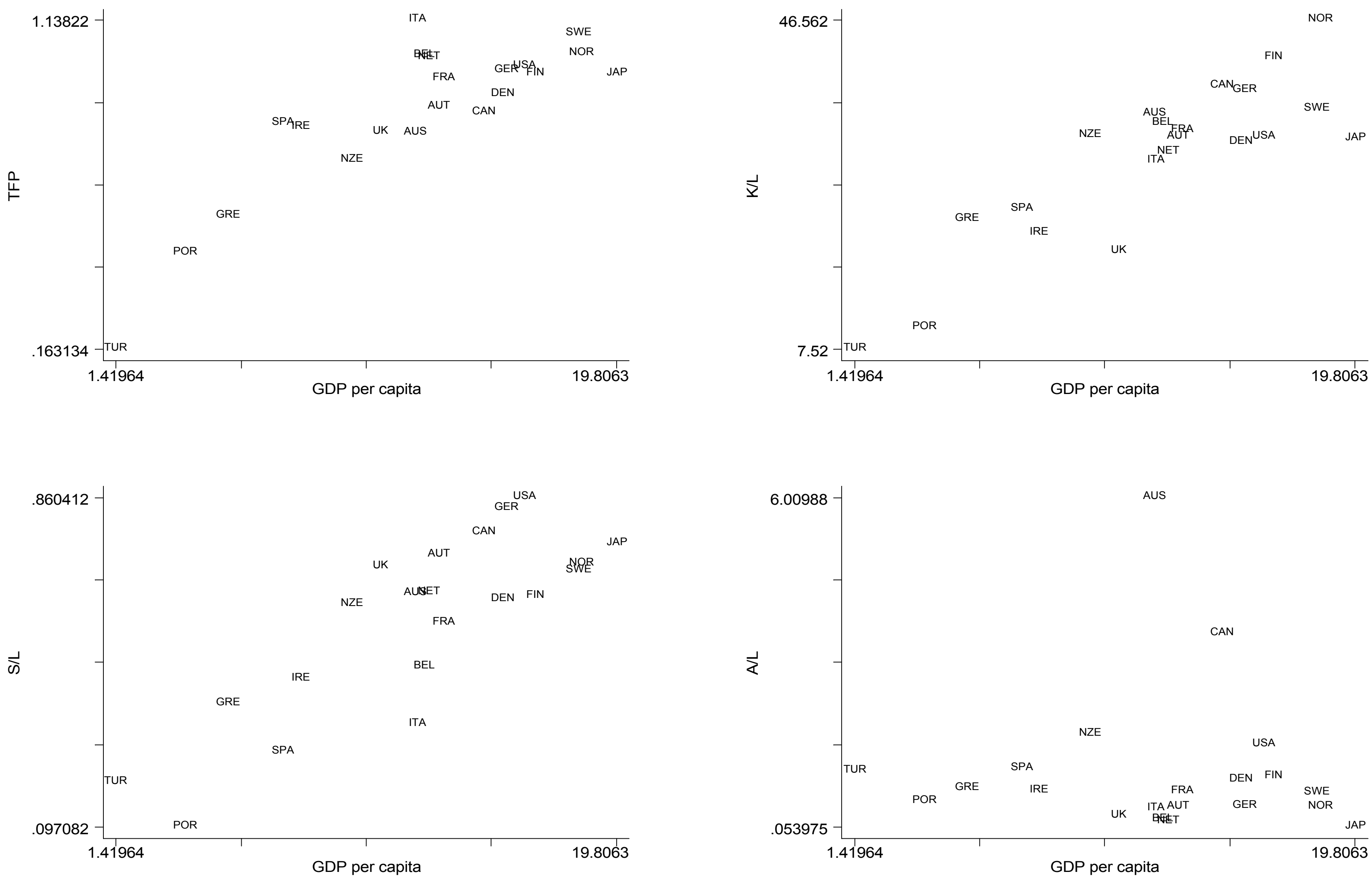
	GDP per cap.	H-N TFP	K/L	S/L	A/L
GDP per cap.	1.00				
H-N TFP	0.85	1.00			
K/L	0.86	0.79	1.00		
S/L	0.83	0.61	0.74	1.00	
A/L	-0.02	-0.14	0.18	0.14	1.00

Table 11. Specification including GDP per capita

Sector	Coeff. on GDP	t-value		Test of joint restrictions F-value	P-value	
Food products	-0.084	0.41		0.16	0.919	
Beverages	-0.060	1.30		0.51	0.682	
Tobacco	-0.091	2.35	**	2.69	0.081	*
Textiles	-0.007	0.15		2.39	0.107	
Wearing apparel	-0.023	1.08		0.48	0.699	
Leather products	-0.004	0.62		0.57	0.641	
Footwear	0.001	0.12		0.81	0.510	
Wood products	0.036	0.84		0.94	0.446	
Furniture, exc. Metal	-0.007	0.26		0.39	0.765	
Paper and products	0.083	0.67		0.10	0.959	
Printing and publishing	0.113	2.06	*	2.19	0.129	
Industrial chemicals	-0.051	0.52		1.60	0.230	
Other chemicals	0.040	0.43		2.17	0.131	
Rubber products	0.006	0.36		1.63	0.221	
Plastic products	0.032	1.09		3.04	0.062	*
Pottery, china, earth.	0.011	1.32		5.24	0.012	**
Glass and products	0.001	0.06		1.57	0.239	
Other non-met.min.pr.	0.006	0.19		1.60	0.231	
Iron and steel	0.049	0.68		0.65	0.595	
Non-ferrous metals	-0.049	1.32		3.41	0.045	**
Fabricated metal prod.	0.069	1.28		1.79	0.192	
Machinery, exc. elect.	0.169	0.95		1.86	0.180	
Machinery electric	0.120	0.78		3.19	0.054	*
Transport equipment	0.198	1.29		1.25	0.326	
Prof. & scient. equip.	0.048	0.87		1.67	0.217	

Table 12. Level of Development and Specialization
Difference: Top 5 countries and Bottom 5 countries

Sector	Observed Shares Bottom Quartile	Observed Shares Top Quartile	Observed Shares Difference	Predicted Shares Difference	Predicted Shares Std.Dev.		Abs. Value Obs. Dif.	Contrib. of Prediction	Abs. Value Error of Pred. Dif.
Food products	3.43	2.50	-0.93	-0.21	0.86		0.93	0.21	0.72
Beverages	1.03	0.52	-0.50	-0.16	0.20		0.50	0.16	0.34
Tobacco	0.55	0.26	-0.28	-0.09	0.19		0.28	0.09	0.19
Textiles	1.93	0.64	-1.29	-1.35	0.21		1.29	1.23	0.06
Wearing apparel	0.70	0.38	-0.32	-0.29	0.09		0.32	0.29	0.03
Leather products	0.11	0.05	-0.06	-0.05	0.03		0.06	0.05	0.01
Footwear	0.20	0.06	-0.14	-0.14	0.05		0.14	0.14	0.00
Wood products	0.41	0.94	0.53	0.34	0.18		0.53	0.34	0.19
Furniture, exc. Metal	0.19	0.37	0.18	0.25	0.11		0.18	0.11	0.07
Paper and products	0.71	2.11	1.40	0.80	0.53		1.40	0.80	0.60
Printing and publishing	0.78	1.90	1.12	0.76	0.26		1.12	0.76	0.36
Industrial chemicals	1.41	1.36	-0.05	0.20	0.42		0.05	-0.20	0.24
Other chemicals	1.64	1.23	-0.41	-0.02	0.39		0.41	0.02	0.39
Rubber products	0.31	0.26	-0.06	-0.03	0.07		0.06	0.03	0.03
Plastic products	0.47	0.64	0.17	0.23	0.13		0.17	0.11	0.06
Pottery, china, earth.	0.20	0.07	-0.13	-0.17	0.04		0.13	0.09	0.04
Glass and products	0.35	0.21	-0.14	-0.11	0.06		0.14	0.11	0.03
Other non-met.min.pr.	1.12	0.76	-0.36	-0.25	0.14		0.36	0.25	0.11
Iron and steel	0.86	1.18	0.32	0.16	0.31		0.32	0.16	0.16
Non-ferrous metals	0.35	0.66	0.30	0.33	0.16		0.30	0.28	0.03
Fabricated metal prod.	0.98	1.84	0.86	0.88	0.24		0.86	0.83	0.03
Machinery, exc. elect.	1.89	3.30	1.41	1.71	0.77		1.41	1.10	0.31
Machinery electric	1.80	2.58	0.78	1.23	0.66		0.78	0.34	0.44
Transport equipment	1.33	2.76	1.43	1.27	0.68		1.43	1.27	0.16
Prof. & scient. equip.	0.35	0.64	0.28	0.26	0.23		0.28	0.26	0.02
						Sum:	13.44	8.83	4.61
								66%	34%



Figures 1, 2, 3 and 4