Specialization, Factor Accumulation and Development

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Abstract

We estimate the effect of factor proportions on the pattern of manufacturing specialization in a cross-section of OECD countries, taking into account that factor accumulation responds to productivity. We show that the failure to control for productivity differences produces biased estimates. Our model explains 2/3 of the observed differences in the pattern of specialization between the poorest and richest OECD countries. However, because factor proportions and the pattern of specialization co-move in the development process, their strong empirical relationship is not sufficient to determine whether specialization is driven by factor proportions, or by other mechanisms also correlated with level of development.

JEL codes F1, F11, O14, O40

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1 Introduction[1]

The Heckscher-Ohlin (H-O) theory states that differences in the pattern of specialization across countries are determined by differences in their factor endowments. It answers the crucial question of what explains trade between countries by focusing on the determinants of sectoral specialization. In this paper we investigate the empirical relationship between factor endowments and specialization. We show that failure to control for the independent influence of productivity differences on output leads to omitted variable bias, in particular since productivity affects incentives to accumulate factors. Our empirical approach eliminates this bias. We show that differences in factor endowments within the OECD can explain two thirds of the difference in the pattern of specialization between the relatively poor and the relatively rich countries in the group. But we also show that, since the identifying variation in relative factor endowments comes from differences across countries in level of development, any economic mechanism that links the pattern of specialization to the stage of development could generate these results.

This paper is related to an extensive empirical literature that estimates the effect of changes in factor endowments on the pattern of specialization. Two main approaches characterize this literature, yielding results that have quite different empirical implications. We provide for the first time a unifying framework that explains why the results of the two approaches are different. The first approach assumes that all countries have access to the same technology. The majority of these studies motivate their estimation strategy by focusing on a very particular case of the H-O theory which yields a linear relationship between sectoral output levels and aggregate factor endowments - the Rybczynski equations [Harrigan (1995), Davis and Weinstein (1998), Reeve (1998), and Bernstein and Weinstein (2002)]. Other studies [Leamer (1987) and Schott (2003)] are less restrictive, but maintain the assumption that technology is identical everywhere. All of these studies find a striking

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regularity: increases in the capital stock are estimated to have a positive and statistically significant impact on output levels in almost all manufacturing sectors. In the words of Harrigan (2001), "Capital is manufacturing's friend." The second approach is represented by Harrigan (1997) and Harrigan and Zakrajšek (2000). Their empirical framework differs from the other studies in that they derive loglinear estimating equations that relate sectoral shares of output to relative factor proportions from a translog approximation to the revenue function. Their specification allows productivity levels to differ across countries. They find that the effect of increases in the relative stock of capital on sectoral output shares is not uniformly positive across sectors. This implies that, as a country accumulates capital, some manufacturing sectors will expand while some others will contract as a share of total output.

In the second section of the paper, we lay out the particular case of the H-O theory used to derive a linear relationship between sectoral output and aggregate factor endowments. We explain how failure to account for cross-country productivity differences leads to a multiplicative form of omitted variable bias in the estimation of these equations. The bias is likely to be important because productivity levels and factor endowments are strongly correlated. We derive productivity-adjusted Rybczynski equations and estimate alternatively standard and productivity-adjusted Rybczynski equations for 25 manufacturing sectors using a cross-section of 21 OECD countries in 1988. We find that the omission of productivity tends to bias upwards the estimated coefficient on capital. This goes a substantial way towards explaining the apparent inconsistency between the results of the two approaches just described.

In the third section of the paper, we transform the linear Rybczynski equations, relating them to a reduced form that expresses output shares as a linear function of factor proportions. This solves the problem that in the standard Rybczynski equations, there is no relevant null hypothesis against which to test the effect of relative factor endowments on specialization. We estimate the reduced form and find 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. The estimated coefficients are consistent with evidence on factor intensities across sectors, even if we are not always able to estimate with precision the independent effects of particular factor ratios on specialization.

In the fourth section of the paper we interpret these results, taking into account the links between development, accumulation and specialization. We note that our evidence of a strong relationship between factor proportions and specialization does not prove that specialization is driven by differences in factor proportions as in the H-O model. Since factor endowments are correlated with level of development through the process of accumulation, any model that links specialization to level of development will predict such an empirical relationship. We briefly describe two plausible alternatives to the H-O model that make this prediction, and we offer suggestions about how future research could test the empirical validity of these alternatives. We point to the relationship between our estimated coefficients and actual sectoral factor intensities as a potentially important piece of evidence.

2 Rybczynski equations and productivity bias

The standard framework used to investigate the empirical relationship between sectoral output and aggregate factor endowments comes from a very special case of the Heckscher-Ohlin theory. Here, we describe and estimate this special case. We show that the failure to control for productivity differences across countries biases the estimated relationship.

2.1 Rybczynski equations

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:

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

where $\widetilde{\mathbf{z}}_j^c$ 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, $\widetilde{\mathbf{z}}_j^c = \widetilde{\mathbf{z}}_j$. That is, unit factor input requirements and unit intermediate input requirements are the same across countries. Denote by $\widetilde{b}_{fj}$ 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. 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. Assume that there are the same number of goods and factors ($J = F$), and that $\widetilde{B}$ 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. These are known as Rybczynski equations. Since prices and 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

$$y_j^c = r_{j0} + r_{j1}v_1^c + \ldots + r_{jF}v_F^c + \varepsilon_j^c \tag{5}$$

for each sector j, where the dependent variable is either gross output or value added. Given that in the data there are more sectors than factors (in our data, we have 25 sectors and four factors: capital, skilled labor, unskilled labor and arable land), the structural interpretation of the constant is the mean effect of omitted factors, and the interpretation of the error term is the deviation from the mean effect of omitted factors. In order for estimates to be unbiased, it must be the case that endowments of omitted factors are uncorrelated with endowments of observed factors.

2.2 Productivity differences and econometric bias

A central assumption of the classic Heckscher-Ohlin model is that technology is identical across countries. However, there is overwhelming evidence that technology differences across countries are important [e.g. Conrad and Jorgenson (1995) and Hall and Jones (1999)]. So far, the empirical literature based on Rybczynski equations has failed to take account of these productivity differences. We show that this failure leads to biased estimates of the relationship between specialization and factor endowments.

Suppose that differences in technology across countries can be represented as Hicks-neutral productivity differences, identical across sectors within a country.[2] Then one unit of factor f in country c is equivalent to a^c units of that factor in a numeraire country. The variables with tildes in Section 2.1 can be reinterpreted as corresponding to factors measured in efficiency units. Then $\widetilde{\mathbf{v}}_j^c = a^c \mathbf{v}_j^c$ where $\mathbf{v}_j^c$ is the vector of unadjusted factors, and the vector of returns to efficiency units of factors is $\widetilde{\mathbf{w}}^c$. Assume that the law of one price holds. 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: i.e. $\widetilde{\mathbf{w}}^c = \mathbf{w} = \mathbf{w}^c / a^c$. Then, efficiency-equivalent unit input requirements for each industry, $\widetilde{b}_{fj}$, 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: $\mathbf{y}^c = R\widetilde{\mathbf{v}}^c = Ra^c\mathbf{v}^c$. They can be estimated by regressing sectoral output on efficiency-equivalent factors:

$$y_j = r_{j0} + r_{j1} a^c v_1^c + \ldots + r_{jF} a^c v_F^c + \varepsilon_j^c \tag{6}$$

[2] Trefler (1995) and Davis and Weinstein (2001) find that accounting for productivity differences significantly improves predictions of the factor content of trade, and that Hicks-neutrality is a good first-order approximation to these technological differences.

When productivity differences across countries are ignored, estimates of the Rybczynski coefficients are subject to a multiplicative form of omitted variable bias as we now demonstrate. Suppose we estimate the misspecified model:

$$\mathbf{y}_j = V\mathbf{s}_j' + \boldsymbol{\eta}_j \tag{7}$$

when the true model is

$$\mathbf{y}_j = AV\mathbf{r}_j' + \boldsymbol{\varepsilon}_j \tag{8}$$

where A is the diagonal matrix with the productivities a^c on the diagonal. The OLS estimate $\hat{\mathbf{s}}_j'$ of the parameter vector is given by

$$\hat{\mathbf{s}}_j' = \left(V'V\right)^{-1} V'AV\mathbf{r}_j' + \left(V'V\right)^{-1} V'\boldsymbol{\varepsilon}_j \tag{9}$$

The expected difference between the estimated parameter vector and the true Rybczynski coefficients $\mathbf{r}_j'$ is

$$E\left(\hat{\mathbf{s}}_j' - \mathbf{r}_j'\right) = \left[\left(V'V\right)^{-1} V'AV - I\right]\mathbf{r}_j' - E\left(V'V\right)^{-1} V'\boldsymbol{\varepsilon}_j \tag{10}$$

Even if we assume that $\boldsymbol{\varepsilon}_j$ is uncorrelated with V, unless $A = I$, i.e. unless there are no productivity differences across countries, this expected difference is non-zero. That is, the estimates $\hat{\mathbf{s}}_j'$ of the Rybczynski coefficients are biased.

In general, it is not possible to sign this bias. If the a^cs were randomly drawn from a distribution with mean 1, independent of factor endowments V, the expected bias would be zero. However, A and V are likely to be correlated. A standard result in traditional growth models is that more productive countries face greater incentives to accumulate capital (physical and human) relative to their labor endowments. If, as the evidence suggests, productivity differences are persistent, 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 should be more capital-abundant. We do indeed observe in the data that endowments V and productivity A are correlated. This implies that the bias we identify is likely to be important. We note further that this type of bias is not specific to linear models of the relationship between specialization and endowments. More generally, it may occur in any specification linking specialization and endowments where productivity differences are not appropriately taken into account.

2.3 Data and estimation results

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 plausible 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 choose value added as our baseline measure of output, but we also check robustness using gross output. In most cases, the results are very similar.

There are four factors in our data set: capital, skilled labor, unskilled labor and arable land. We use non-residential capital, from the Penn World Tables (PWT), as our measure of the capital stock. The labor force is also 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.[4] The rest of the labor force is considered unskilled. Arable land comes from FAO.

We need a measure of Hicks-neutral TFP differences (a^c) across countries to estimate (6). We construct a TFP measure that is consistent with the hypothesis of conditional factor price equalization.[5] Conditional factor price equalization and Hicks-neutrality together imply that for any factor 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,

[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 are very incomplete.

[4] The OECD classification "Senior cycle second level" corresponds approximately to those who have attended beyond 10th grade in the US education system.

[5] We obtain very similar results using alternative measures that do not rely on conditional FPE.

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, with information on factor returns in the US, we can calculate a^c as

$$a^c = \frac{Y^c}{\sum\limits_{f=1}^{F} v_f^c w_f^{US}} \tag{11}$$

To calculate factor returns for the US, we divide total factor income for each factor by the relevant factor endowment. The details are described in Appendix B.

Summary statistics of sectoral value added shares are reported in Table 1. They show that there are indeed cross-country differences in production structure. Endowment data unadjusted for productivity differences are reported in Table 2 in the form of factor abundance ratios $\left(v_f^c/v_f^w\right)/(Y^c/Y^w)$, where Y denotes GDP, and the superscript w denotes the world (i.e., all the countries in the sample). We report the FPE-consistent measure of TFP in Table 2. More productive countries appear to be scarce in all factors because output is high relative to endowments. Less productive countries appear to be abundant in all factors because output is low relative to endowments. This is Trefler's (1995) "endowments paradox."

We first estimate (5), the unadjusted Rybczynski equations, sector by sector. Since all variables are in levels, we weight each observation by the inverse of GDP to correct for size-related heteroskedasticity. Table 3 shows the results. We reproduce the only finding that is consistent across all studies using the linear Rybczynski framework: the coefficient on capital is systematically positive, and frequently significantly positive [Harrigan (1995), Davis and Weinstein (1998), Reeve (1998), and Bernstein and Weinstein (2002)]. As noted in the introduction, this is also true in studies that work with larger samples of countries, and do not assume a uni-cone model [Leamer (1987) and Schott (2003)].[6]

Using the productivity measure to obtain factor endowments in efficiency units, we then estimate (6), the productivity-adjusted Rybczynski equations, implementing the same heteroskedasticity correction as before. The results are reported in Table 4. They are

[6] Schott (2003) finds this for the only cone with a substantial number of observations.

strikingly different from those in Table 3 in one main respect: the coefficient on capital is no longer systematically positive, indeed it is more often negative than positive. This confirms our priors about the existence of a productivity bias. In addition, the striking difference between the two sets of estimates indicates that the magnitude of the bias is not trivial.[7]

Three independent additional pieces of evidence are consistent with the existence of this bias. First, Bernstein and Weinstein (1998) estimate equation (5) for both a sample of OECD countries and for Japanese regions. In the case of the OECD (in contrast to the Japanese regions), the coefficient on capital is positive and significant in most manufacturing sectors. Since technology differences across Japanese regions (in contrast to OECD countries) are probably small, the bias is also 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 systematically positive and significant coefficients on capital in most manufacturing sectors. Finally, Turkey is an outlier in our sample in terms of productivity. When we exclude it in the estimation of (5), the strong pattern of positive and significant coefficients on capital is considerably reduced. But when we exclude it from the estimation of (6), the results do not change.

3 Heckscher-Ohlin reduced form

Despite the simplicity of their linear form, Rybczynski equations, whether corrected for productivity differences or not, are still a knife-edge result derived under very strong assumptions. In particular, they require an equal numbers of goods and factors, absence of trade costs, and (conditional) factor price equalization. The reason for their popularity with empirical trade researchers is that the Heckscher-Ohlin theorem, in its classic generalized formulation (see Deardorff (1982)), does not provide a clear alternative since it does not yield empirical predictions at the sectoral level.

[7] Harrigan (1995) gets positive and significant coefficients on capital when he runs the Rybczynski regression on a panel with fixed effects. In this case, there is probably a cyclical correlation between factors and omitted productivity.

However, the restrictiveness of the assumptions used to derive them is not the only problem with the empirical implementation of Rybczynski equations as presented above. First, the estimated coefficients are hard to interpret in the spirit of the H-O theorem because they are silent on how differences in factor proportions affect the pattern of specialization, (i.e. the relative importance of each sector in total GDP). For example, a Rybczynski coefficient of r_{jf} for capital in the *Beverages* sector indicates that an increase of one unit in the *absolute level* of the capital stock induces an increase of r_{jf} in the *absolute level* of production in that sector. But this information alone cannot say whether, as a result of capital accumulation, the production of *Beverages* will increase or decrease as a share of GDP. Second, without appropriate rescaling, Rybczynski equations fail to nest the obvious alternative hypothesis that sectoral output levels depend on country size alone: if larger countries have larger factor endowments and tend to produce larger quantities in every sector, we will still estimate some positive and possibly significant coefficients on endowments in (6), even if *relative* endowments play no role as determinants of specialization. The estimated coefficients will just capture this size effect.

The approach we take to these problems is to propose and estimate a reduced form relationship between sectoral output and endowments that captures more closely the intuition of the H-O theory, but still preserves a close relation to the Rybczynski estimates. This reduced form relates *relative* sectoral output (i.e. specialization) to *relative* factor abundance (i.e. factor proportions):

$$\frac{y_j^c}{GDP^c} = \beta_{j0} + \beta_{jK}\frac{K^c}{L^c} + \beta_{jS}\frac{S^c}{L^c} + \beta_{jA}\frac{A^c}{L^c} + \epsilon_j^c \tag{12}$$

where $L^c = S^c + U^c$ is total labor in country c. Note that for four factors, there are only three measures of relative factor abundance. This specification has the distinct advantage over the standard Rybczynski equations that it nests a meaningful alternative hypothesis to the Heckscher-Ohlin theory: if the level of output depends on size alone, this should be captured by the constant term, while the coefficients on the factor proportions should be zero. In addition, as long as productivity differences are Hicks-neutral and identical across sectors and factors within a country, (12) does not suffer from productivity bias of the type described in the previous section.[8] Lastly, (12) has the desirable feature that it is very similar to a transformation of the Rybczynski equations (6). To see this, drop the constant term in (6)[9] and divide by $a^c L^c$ to obtain

$$\frac{y_j^c}{a^c L^c} = r_{jK}\frac{K^c}{L^c} + r_{jS}\frac{S^c}{L^c} + r_{jU}\frac{U^c}{L^c} + r_{jA}\frac{A^c}{L^c} + \varepsilon_j^c. \tag{13}$$

Since $S^c/L^c + U^c/L^c = 1$ there is no independent variation between these two regressors.[10] We can solve for U^c/L^c and substitute into (13) to obtain:

$$\frac{y_j^c}{a^c L^c} = r_{jU}^c + r_{jK}\frac{K^c}{L^c} + (r_{jS} - r_{jU})\frac{S^c}{L^c} + r_{jA}\frac{A^c}{L^c} + \varepsilon_j^c \tag{14}$$

There are two points to note about (14). First, the results from estimating (14) can be recovered from (6) if this last equation is estimated omitting the constant and using weights proportional to adjusted labor. Second, (14) and (12) are identical except for the denominator of the dependent variable. Empirically, the two specifications yield very similar estimates as the correlation between $a^c L^c$ and GDP^c is 0.9987. This implies that a transformation of the Rybczynski coefficients and their standard errors can be given a reduced form interpretation in the spirit of the H-O theorem. It is this feature that motivates us to work with this particular reduced form. Alternative specifications are otherwise equally plausible, and it is not our goal here to assess which fits the data best.[11]

3.1 Reduced form estimates

The results from estimating (12) are reported in Table 5. We do not report the results from estimating (14), but they are very similar. When we use gross output instead of value

[8] With forms of productivity differences other than Hicks-neutrality, the productivity adjustment would not necessarily cancel out in factor endowment ratios.

[9] For most sectors, inclusion or exclusion of the constant term does not significantly affect the results.

[10] This particular restriction is an artifact of the factors we use. But taking into account that aggregate output depends on factor endowments, rescaling by GDP^c instead of $a^c L^c$ would also result in linear dependence among all four independent variables.

[11] Harrigan and Zakrajšek (2000) estimate a similar (loglinear) specification derived from a translog approximation to the revenue function that is not subject to any of the problems that we have pointed out so far. The qualitative results from estimating the log-linear version of (12) using our data are very similar to those from estimating (12).

added as the dependent variable, the results are also almost unchanged. No one country drives the results. In particular, when Turkey is excluded the results do not change, except for a loss of precision on average. We test for the presence of nonlinearities by including quadratic terms for each variable (we do not have sufficient degrees of freedom to include also interaction terms). For only one sector can we reject (at the 10% level) the restriction that the coefficients on the non-linear terms are jointly zero.

Except in the 2-good, 2-factor case, the Heckscher-Ohlin theory does not guarantee a monotonic relationship between the sector-specific coefficients we have estimated and sectoral factor intensities. However, we find that an interesting empirical relationship does in fact exist. Sectoral factor intensities for US manufacturing are reported in Table 6. Considering only those sectors with coefficients significantly different from zero, the sign of the estimated coefficient on a particular factor in a particular sector in Table 5 tends to match the actual intensity of factor use in that sector. Most of the positive significant coefficients on S/L are in sectors that use skilled labor intensively. The two negative significant coefficients on S/L are in *Leather Products* and *Footwear*, two of the sectors with the lowest skill intensity. For K/L, most of the negative significant coefficients are in sectors with low capital intensity, while the only positive and significant coefficient is in *Non-ferrous metals*, a capital intensive sector. Figure 1 is a scatter-plot of the estimated coefficients on S/L against the actual skill intensity in the US. The relationship between the coefficients we estimate and sectoral factor intensities is in fact very strong. Figure 2 graphs the estimated coefficient on the K/L ratio against the sectoral capital intensity. Capital intensive sectors do not tend to have positive estimated coefficients on the K/L ratio.

The basic mechanism of the H-O theory suggests that the more abundant is a country in a particular factor, the lower is the autarky price of that factor, the cheaper is the autarky price of goods intensive in that factor, and hence the stronger the comparative advantage and specialization of the country in those goods. However, despite its appeal, this intuition need not always carry through for all goods [See Deardorff (1979) and Aw (1983)]. Examining the match between estimated coefficients and factor intensities tests not the H-O theory, but something stronger. The existence of a strong positive correlation for the share of skilled labor poses a challenge for future research: Are there stronger versions of the H-O theory that can explain this finding?[12]

3.2 Prediction

As the R-squared indicates, the ability of variation in relative factor endowments to explain variation in the share of total output in individual sectors differs a lot across sectors. We want a measure of the ability of relative factor endowments to explain the pattern of specialization as a whole. In our cross-section data-set, most of the variation in relative factor endowments across countries is between relatively poor and relatively rich countries. As a summary measure of the ability of relative factor endowments to explain the pattern of specialization across the OECD, we compare the actual difference in pattern of specialization between rich and poor countries with that which would be predicted by the model, conditional on the endowments of rich and poor countries. The exercise is performed as follows. 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 groups, "poor" and "rich", we use the estimated model (12) 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 7. 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 countries 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

[12] Romalis (2003) provides a model with imperfect competition, trade costs, and two types of countries. In this case, 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.

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 change in specialization pattern 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 a measure of the implied inter-sectoral reallocation of output shares 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 among 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.

4 Specialization and development

4.1 Factor accumulation 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 3, 4, 5 and 6 plot TFP and the three measures of factor abundance against GDP per capita. These plots are consistent with different OECD countries being at different points along similar paths of development. As GDP per capita rises countries accumulate capital and skilled labor, the capital-labor ratio rises, the share of skilled labor in total labor rises and TFP also increases. We cannot 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 comovement. First, our independent variables are not linearly dependent, but there is nevertheless a systematic relationship between them. In particular, the correlation between K/L and S/L is 0.74. Given this correlation and the small sample size, it is not surprising that we cannot always identify with precision the independent effect of changes in K/L and changes in S/L on the pattern of specialization in Table 5. What we identify is the common effect of moving along a similar path of development.

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 can be shown by including GDP per capita as an independent variable in our reduced form specification:

$$\frac{y_j^c}{Y^c} = \beta_{jU}^c + \beta_{jK}\frac{K^c}{L^c} + \beta_{jA}\frac{A^c}{L^c} + \beta_{jS}\frac{S^c}{L^c} + \frac{Y^c}{POP^c} + \epsilon_j^c \tag{15}$$

In Table 8 we report the estimated coefficients and t-statistics on GDP per capita. In only two sectors does GDP per capita add explanatory power after relative factor endowments have been controlled for. We also 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 this joint restriction at the 10% level or lower. When both factor proportions and GDP per capita are included, we cannot estimate with precision the independent effect of each, because they are strongly correlated. But when sectoral shares are regressed on each independently, the estimated effect on specialization of both factor proportions and GDP per capita is statistically significant in a number of sectors. In unreported results, we find that for factor proportions, we can reject the restriction that the coefficients on *all* regressors in (12) are equal to zero in 12 sectors. Similarly, the coefficient on GDP is significant in 12 sectors when we regress sectoral value added shares on GDP per capita alone.

The existence of a strong relationship between GDP per capita and pattern of specialization has been noted for decades [e.g., Chenery (1960), Leamer (1974), Harrigan and Zakrajšek (2000)]. However, so far it has not explicitly been noted that this relationship calls into question whether the power of factor proportions to predict specialization can be used as evidence in favor of the Heckscher-Ohlin theory of specialization. Using (15) alone, it is not possible to say whether specialization and relative factor endowments are each independently determined by the level of development, or whether the level of development determines relative factor endowments, and these in turn drive the pattern of specialization. We now develop this argument.

4.2 Alternative hypotheses linking specialization and development

Any model in which both factor accumulation and specialization are systematically related to development will generate a reduced form similar to (12). We suggest two plausible alternatives to the Heckscher-Ohlin theory that make similar predictions. First, suppose that as countries become richer, TFP increases and physical and human capital accumulate. Suppose also that there are inter-sectoral non-homotheticities in consumption [e.g. as in Hunter and Markusen (1988)]. That is, more developed (i.e. richer) countries 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 necessarily be correlated with consumption patterns. In such a world, we would observe a correlation between the pattern of specialization and relative factor endowments, even without any Heckscher-Ohlin mechanism at work.

A model of specialization based on Ricardian productivity differences alone could also generate a correlation between factor endowments and specialization. Suppose that richer countries are on average more productive than poorer countries, but that the productivity differential is not uniform across sectors. Then richer countries will have a comparative advantage (driven by Ricardian differences) in the sectors with the highest productivity differentials, and they will tend to specialize in these sectors. At the same time, since richer countries have a higher aggregate productivity, they will be more capital and skilled-labor abundant. As a result, there will be a systematic correlation between factor endowments and specialization even if there is no causal link between the two.

Since both of these models (and potentially others) can generate correlations between specialization and factor endowments similar to those in a Heckscher-Ohlin world, the finding that factor proportions are good predictors of specialization does not allow us to distinguish between these alternative theories. Identification must come from testing predictions that differ across different alternative hypotheses. For example, if non-homotheticities in consumption drive specialization, sectors in which rich countries specialize should have high income elasticities of demand, and sectors in which poor countries specialize should be income inelastic. Alternatively, if Ricardian technology differences are the driving mechanism, sectors in which rich countries specialize should be those with relatively large productivity differences between countries at different stages of development. Finally, we note that the preferred theory of specialization should be able to explain the positive correlation demonstrated in Figure 1: Is it a coincidence that the sectors in which rich countries specialize are more skilled-labor intensive? We see this as a promising direction for future research.

5 Conclusion

This paper addresses an old question: How do relative factor endowments affect specialization? In the trade literature, in contrast to the growth literature, relative factor endowments are usually taken as given. But they are in general 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 is exacerbated because productivity affects factor accumulation, and hence differences in productivity are correlated with differences in factor endowments. We adjust the classic Rybczynski 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, 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.

A Appendix: Data sources and construction

A.1 Endowments

The capital stock in 1988 comes from the PWT. Investment series for different types of capital are converted into million dollars using the corresponding investment PPPs. To estimate the capital stock, we use the perpetual inventory method with the depreciation rates used by the PWT: 3.5% for construction, 15% for machinery and 24% for transport equipment.

The labor force in 1988 also comes from the PWT. It is measured in thousand persons. To obtain skilled and unskilled labor, we use data on educational attainment from the OECD publication *Education at a Glance* (1992 and 1993).[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. We combine information

[13]We believe that the Barro-Lee data-set, though standard in the literature, mismeasures vocational education and as a result underestimates educational attainment in European countries which form an important part of our sample.

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.

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 because many countries do not report data on these sectors. 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). To be consistent with our exclusion of 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 use data on factor prices. 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 shares 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 above are skilled.

B Appendix: Productivity estimates

We calculate productivity levels as in (11). 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 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, then $w_u U + 1.63\,(w_u)\,S =$ Total compensation of labor. From this we can back out w_u and hence w_s. We 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. For the US in 1988, we estimate factor prices of \$ 15877 for unskilled labor (w_u), \$ 25952 for skilled labor (w_s), \$ 143 per hectare for arable land, and \$ 0.266 per dollar of capital stock, inclusive of depreciation.

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Table 1. Summary statistics of output data; Avg. and variation of value added shares across 21 OECD countries

Sector[a]	Description	Average share[b]	Coeff. of variation
311	Food products	2.97	0.52
313	Beverages	0.72	0.52
314	Tobacco manufactures	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] 3-digit ISIC code

[b] Sectoral value added as a share of GDP

Table 2. Factor Abundance and TFP
The endowments paradox

Country	Capital[a]	Skilled[a]	Unskilled[a]	Land[a]	TFP[b]	GDP/Pop[c]
JAP	0.986	1.016	0.708	0.051	0.98	19.81
NOR	1.206	0.811	0.723	0.331	1.04	18.52
SWE	0.962	0.820	0.782	0.546	1.10	18.38
FIN	1.221	0.815	1.010	0.864	0.98	16.82
USA	0.932	1.089	0.377	1.353	1.00	16.44
GER	1.071	1.038	0.437	0.364	0.99	15.74
DEN	1.081	0.935	1.199	0.945	0.92	15.61
CAN	1.238	1.104	0.672	3.496	0.86	14.92
FRA	1.082	0.814	1.321	0.699	0.97	13.45
AUT	1.108	1.093	0.880	0.426	0.88	13.28
NET	0.940	0.865	1.036	0.134	1.03	12.92
BEL	1.068	0.646	1.564	0.179	1.03	12.75
ITA	0.918	0.458	1.937	0.368	1.14	12.48
AUS	1.288	1.028	1.249	6.752	0.80	12.43
UK	0.810	1.311	1.201	0.320	0.81	11.12
NZE	1.394	1.154	1.553	2.268	0.72	10.07
IRE	0.949	0.871	2.364	0.976	0.82	8.20
SPA	1.097	0.548	3.144	1.567	0.83	7.55
GRE	1.512	1.118	3.857	1.526	0.56	5.53
POR	1.095	0.467	9.258	1.728	0.45	3.95
TUR	2.193	2.599	22.061	9.577	0.16	1.42
Coef. of variation	0.254	0.444	1.769	1.440	0.270	1.933

[a] Factor abundance is calculated as: $(v_f^c/v_f^w) / (Y^c/Y^w)$

[b] TFP is calculated as described in Equation 10

[c] In thousands of 1988 US$

Table 3. Unadjusted Rybczynski equations[a]

Sector	Capital[b]	t	Skilled[b]	t	Unsk.[b]	t	Arable[b]	t	Cons.[b]	t	N	R^{2c}
Food products	2.63	0.27	839.55	1.81 *	-209.42	2.52 **	-3.88	0.07	1290	3.98 **	21	0.64
Beverages	1.42	0.51	179.80	1.35	-33.45	1.40	-5.66	0.34	94	2.63 **	21	0.57
Tobacco manuf.	-0.64	0.27	227.38	2.03 *	27.28	1.36	-19.42	1.40	-11	0.14	21	0.64
Textiles	9.85	2.73 **	-128.72	0.75	117.70	3.82 ***	-35.37	1.66	18	0.15	21	0.79
Wearing apparel	4.42	2.48 **	-11.97	0.14	0.01	0.00	-3.28	0.31	36	0.61	21	0.72
Leather products	1.44	3.29 ***	-37.23	1.83 *	1.36	0.38	-2.17	0.86	3	0.20	20	0.56
Footwear	2.77	3.24 ***	-85.54	2.15 **	8.06	1.14	-5.16	1.05	-2	0.07	20	0.50
Wood products	6.09	2.13 **	-34.76	0.26	-57.47	2.35 **	10.98	0.65	61	0.64	21	0.63
Furniture, exc. Metal	3.91	2.27 **	57.81	0.71	-29.50	2.01 *	-10.91	1.07	-48	0.83	21	0.76
Paper and products	13.28	1.61	-53.10	0.14	-70.75	1.00	-15.47	0.32	3	0.01	21	0.46
Printing and publ.	5.93	1.30	435.54	2.01 *	-130.58	3.36 ***	-11.56	0.43	65	0.42	21	0.81
Industrial chemicals	9.35	1.37	437.58	1.35	27.30	0.47	-89.04	2.21 **	-204	0.90	21	0.72
Other chemicals	-2.21	0.34	679.80	2.17 **	-61.38	1.09	-37.21	0.96	329	1.50	21	0.55
Rubber products	1.74	1.60	69.77	1.36	1.18	0.13	-9.33	1.46	-51	1.40	21	0.77
Plastic products	2.65	1.07	221.47	1.93 *	-42.62	2.10 *	-14.77	1.04	-26	0.32	20	0.78
Pottery, china, earth.	1.67	2.39 **	-26.37	0.83	21.11	3.80 ***	-10.19	2.61 **	-25	1.10	19	0.71
Glass and products	0.89	0.78	66.71	1.26	5.91	0.63	-8.76	1.34	21	0.56	20	0.65
Oth. non-met.min.pr.	4.76	1.67	161.96	1.22	-2.29	0.10	-26.42	1.61	74	0.80	20	0.77
Iron and steel	8.84	2.60 **	230.99	1.43	23.88	0.82	-45.02	2.21 **	-385	3.39 ***	20	0.87
Non-ferrous metals	7.08	3.05 ***	-61.88	0.56	-49.34	2.49 **	18.04	1.30	-110	1.42	20	0.78
Fab. metal prod.	11.24	2.44 **	372.25	1.74	-97.74	2.57 **	-40.47	1.53	-156	1.05	20	0.87
Mach. exc. elect.	2.28	0.17	1424.35	2.32 **	-149.10	1.37	-141.63	1.87 *	165	0.39	20	0.69
Machinery electric	4.09	0.34	1232.36	2.22 **	-75.39	0.77	-152.51	2.22 **	-95	0.25	20	0.69
Transport equipment	19.97	1.92 *	524.91	1.09	-99.37	1.16	-74.40	1.25	-826	2.47 *	20	0.78
Prof. & sci. equip.	-3.33	0.87	368.01	2.08 *	-44.21	1.41	-13.10	0.60	132	1.07	20	0.41

* indicates significant at the 10% level, ** at the 5% level and *** at the 1% level

[a] Dependent variable is sectoral value added. Observations are weighted by the inverse of GDP to correct for heteroskedasticity.

[b] Constant is divided by 1000000, other coefficients by 1000.

[c] R-squared = 1-SSR/SST where SSR is sum of squared residuals, SST is n times sample variance of dep. variable, calculated from weighted model

Table 4. Productivity-adjusted Rybczynski equations[a]

Sector	Capital[b]	t		Skilled[b]	t		Unsk.[b]	t		Arable[b]	t		Cons.[b]	t		N	R^2[c]
Food products	-3.82	-0.32		117	2.05	*	-28	-0.12		24.2	0.37		118	3.91	***	21	0.68
Beverages	-2.40	-0.71		33	2.07	*	69	1.00		5.6	0.30		21	2.48	**	21	0.63
Tobacco manuf.	-5.58	-1.57		42	2.44	**	148	2.03	*	-12.9	-0.66		0	-0.01		21	0.51
Textiles	-9.29	-2.72	**	55	3.34	***	652	9.33	***	0.9	0.05		-5	-0.55		21	0.89
Wearing apparel	-1.71	-0.92		21	2.35	**	159	4.20	***	13.5	1.32		2	0.37		21	0.82
Leather products	0.69	1.26		-1	-0.52		25	2.36	**	-0.2	-0.08		0	0.10		20	0.60
Footwear	0.76	0.76		-2	-0.34		65	3.37	***	-0.3	-0.06		-1	-0.48		20	0.61
Wood products	4.79	1.38		3	0.18		-68	-0.95		24.6	1.28		10	1.18		21	0.68
Furniture, exc. Metal	2.43	1.13		12	1.15		4	0.09		-4.4	-0.37		-3	-0.57		21	0.77
Paper and products	10.29	0.99		9	0.18		-81	-0.38		7.8	0.14		12	0.45		21	0.49
Printing and publ.	-0.62	-0.13		75	3.22	***	-33	-0.33		15.3	0.57		6	0.48		21	0.87
Industrial chemicals	-4.87	-0.63		101	2.70	**	410	2.57	**	-69.0	-1.60		-22	-1.08		21	0.78
Other chemicals	-13.45	-1.83	*	118	3.36	***	180	1.20		-15.1	-0.37		22	1.18		21	0.67
Rubber products	-1.72	-1.50		20	3.66	***	92	3.93	***	-1.9	-0.31		-6	-2.09	*	21	0.85
Plastic products	-2.92	-1.12		46	3.75	***	62	1.23		-0.9	-0.06		-4	-0.66		20	0.86
Pottery, china, earth.	-0.63	-1.07		5	1.93	*	97	8.56	***	-7.0	-2.23	**	-4	-2.57	**	19	0.87
Glass and products	-1.98	-1.64		18	3.12	***	85	3.62	***	-3.6	-0.55		0	0.15		20	0.77
Oth. non-met.min.pr.	-4.09	-1.43		50	3.72	***	220	3.97	***	-6.6	-0.43		4	0.64		20	0.87
Iron and steel	-2.08	-0.45		64	2.85	**	342	3.59	***	-25.7	-0.99		-37	-3.08	***	20	0.85
Non-ferrous metals	5.50	1.69		-1	-0.09		-22	-0.33		32.4	1.78	*	-5	-0.60		20	0.75
Fab. metal prod.	1.40	0.29		80	3.53	***	71	0.75		-12.3	-0.48		-11	-0.91		20	0.92
Mach. exc. elect.	-7.17	-0.46		194	2.67	**	36	0.12		-130.1	-1.57		14	0.37		20	0.75
Machinery electric	-14.08	-1.04		207	3.25	***	272	1.03		-132.0	-1.82	*	-14	-0.41		20	0.77
Transport equipment	-4.47	-0.40		152	2.87	**	408	1.86	*	-11.3	-0.19		-82	-3.01	***	20	0.85
Prof. & sci. equip.	-6.00	-1.28		52	2.36	**	-23	-0.25		-7.3	-0.29		9	0.81		20	0.48

* indicates significant at the 10% level, ** at the 5% level and *** at the 1% level

[a] Dependent variable is sectoral value added. Observations are weighted by the inverse of GDP to correct for heteroskedasticity.

[b] Indep. vars are raw factors multiplied by TFP. Const. is divided by 10000000, coeffs. on capital, unskilled and arable by 1000, on skilled by 10000.

[c] R-squared = 1-SSR/SST where SSR is sum of squared residuals, SST is n times sample variance of dep. variable, calculated from weighted model

Table 5. Reduced form specification[a]

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

* indicates significant at the 10% level, ** at the 5% level and *** at the 1% level

[a] Dependent variable is sectoral value added as a share of total value added

[b] All coefficients are divided by 1000.

Table 6. 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 manuf.	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 in the US, 1988.

[b] Expressed relative to the K/L ratio for US manufacturing as a whole.

Table 7. Level of Development and Specialization
Difference: Top 5 countries and Bottom 5 countries

	Observed Shares[a]			Predicted Shares[a]					
Sector	Bottom Quartile	Top Quartile	Difference	Difference	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 manuf.	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%

* indicates significant at the 10% level, ** at the 5% level and *** at the 1% level

[a] All values are expressed as percentages.

Table 8. Reduced form specification including GDP per capita[a]

Sector	Coeff. on GDP/Pop	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 manuf.	-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

* indicates significant at the 10% level, ** at the 5% level and *** at the 1% level

[a] Dependent variable is sectoral value added as a share of total value added. Relative factor endowments are included as dependent variables but coefficients are not reported.

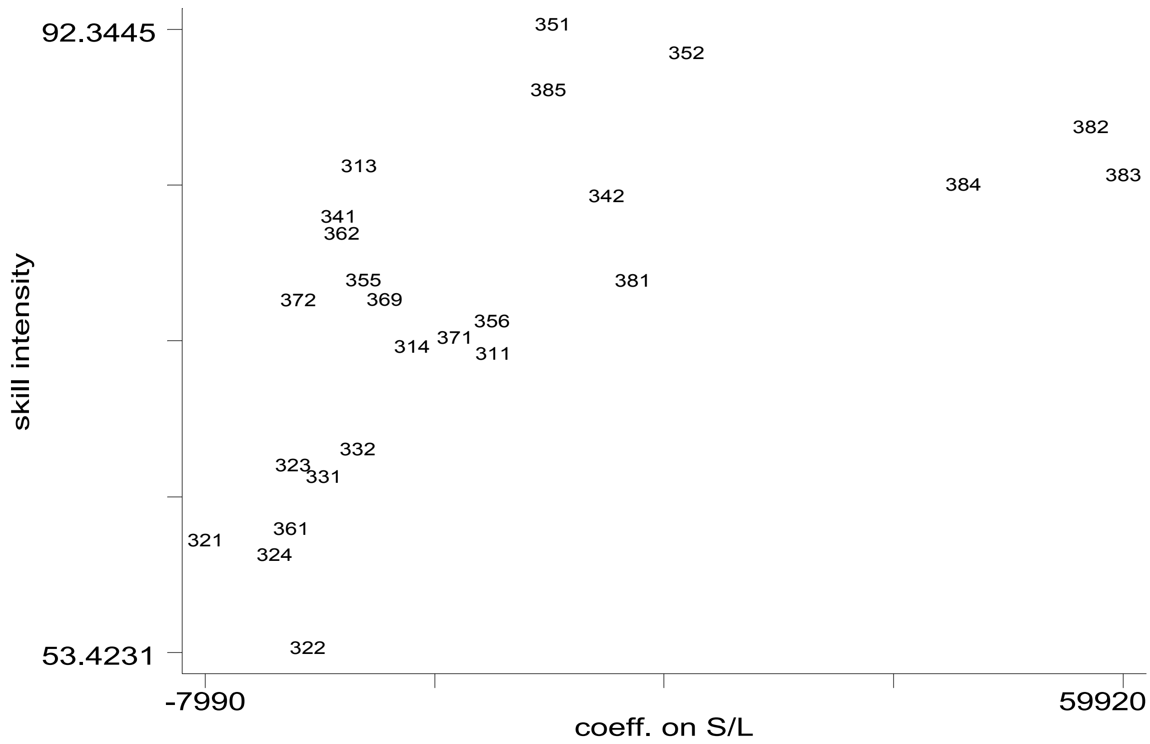


Figure 1.

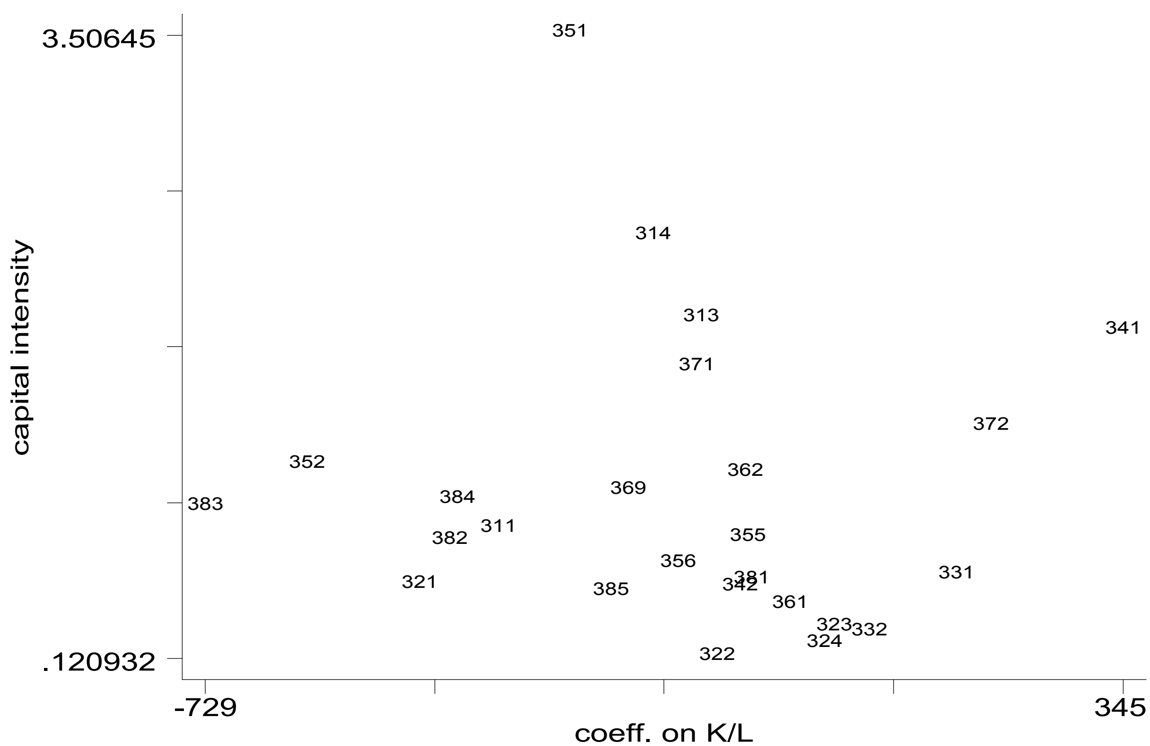
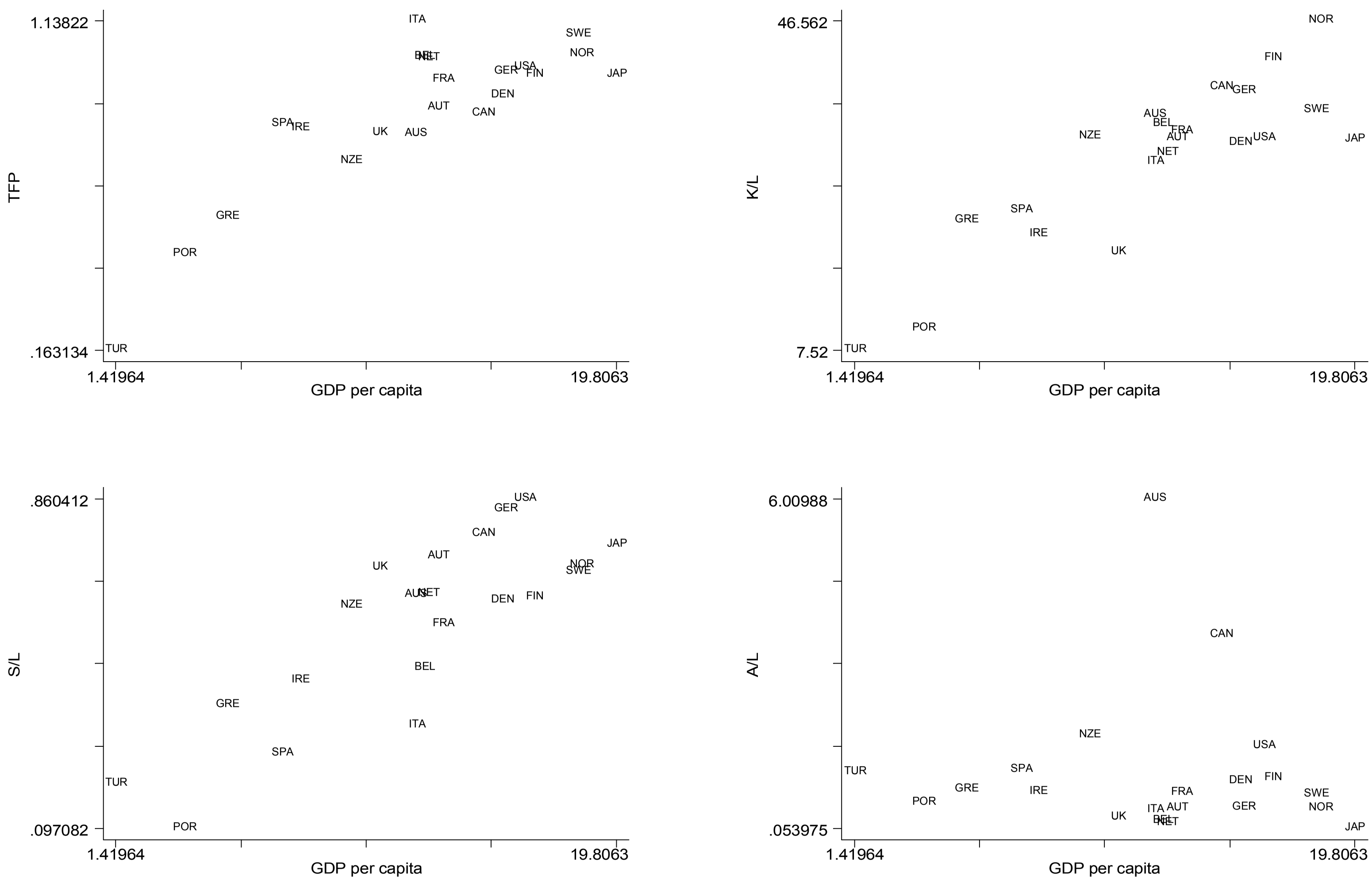


Figure 2.



Figures 3, 4, 5 and 6.