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"Capital and Specialization: The Role of Productivity Differences, Accumulation and Financial Integration"

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Capital and Specialization:
The Role of Productivity Differences, Accumulation and Financial Integration

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Abstract

The empirical literature on the determinants of international specialization has concluded that capital is crucial, while other factors do not play a major role. This contradicts the intuition of many economists that, due to financial integration, capital endowments are no longer an important determinant of the distribution of production. We show that the empirical results of much of the previous literature are biased by the failure to control for productivity differences across countries and their effects on factor accumulation. We control for productivity differences. We find that skilled and unskilled labor are important determinants of the pattern of international specialization, but capital is not. We argue that this is consistent with a world where, because of international financial integration, production is determined mainly by the distribution of skilled and unskilled labor.

1 Introduction

Understanding why countries specialize and trade with each other is the most fundamental problem in international trade. Before we are able to address the effects of trade liberalization, the imposition of tariffs, or the integration of world markets, we must understand how the international structure of production is determined.

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Over the last fifty years, the Heckscher-Ohlin (H-O), or factor proportions theory has been the dominant theory of international specialization. One of the most appealing features of this theory, in contrast to the Ricardian theory (for example), is that its predictions on specialization and trade are directly linked to observables: factor intensities and factor endowments. As a result, the H-O theory has been the basis for most empirical work on the determinants of specialization. Most of this work has proceeded as follows: Under the assumptions that factor prices are equalized across countries and that the number of goods is equal to the number of factors, the H-O theory predicts an identical linear relationship between output and factor endowments in all countries. The parameters of this linear relationship can be estimated by regressing sectoral output on endowments. Harrigan (1995), Davis and Weinstein (1998a), Bernstein and Weinstein (1998), and Reeve (1998) do this. They use data for OECD countries, where the assumption of factor price equalization (FPE) is more likely to hold. In the more general case where FPE does not hold, countries are in different cones of specialization according to their pattern of factor abundance. In this case, the relationship between sectoral production and endowments is nonlinear.[1] The multi-cone model is empirically explored by Leamer (1987) and Schott (1999) using a broader sample of countries.

A striking result common to all of these studies is that capital appears to be the most important determinant of specialization. In the papers that estimate the linear model, the coefficient on capital is significant in most sectors. The coefficients on other factors such as skilled and unskilled labor are much less often significant. Additionally, in the linear model, the coefficient on capital is positive for almost all manufacturing sectors. The positive effect of capital shows up also in the non-linear models of Leamer and Schott. No such strong regularity across papers and specifications is observable for other factors. The results of this literature strongly suggest that capital is the main determinant of specialization, and that the role of the other factors is less important.

These results are puzzling. They are puzzling first, because we do not expect the coefficient on capital to be significantly positive in almost all manufacturing sectors, and few of the coefficients on the other factors to be significant. In particular, the results do not accord with our intuition about factor intensity in several sectors. For example, we would expect the total endowment of unskilled labor to be important in determining production for sectors like Wearing apparel, and Footware, and skilled labor to be important for sectors like Non-electrical and Electrical machinery. Second, they contradict the view that international capital mobility has dampened the importance of capital as a determinant of the pattern of international specialization. For example, this view implicitly underlies the intuition of many economists in the recent debate over the effect of globalization on employment and wage dispersion in the US. Their arguments are generally based on a two factor

[1] Within each cone FPE holds and linearity is preserved. The two sets of studies are consistent as long as all OECD countries belong to the same cone.

model where skilled and unskilled labor are the two factors.[2] Wood (1994) explicitly argues the case that capital does not matter for specialization, on the grounds that (apart from structures), capital goods are tradeable, and financial capital is fairly mobile. This view is also clearly stated by Sachs and Shatz (1994), who argue that "capital is internationally mobile and therefore not a restraining factor in manufacturing production in low-wage and, initially, capital scarce economies".

Our task in this paper is to explore these puzzling results. We proceed within the framework used by previous work, that is, we assume that endowments are an important determinant of the pattern of specialization. We think carefully about how technology differences across countries, factor accumulation and factor mobility might affect this relationship. First, we note that technology differences across countries are important. While the literature on testing the Heckscher-Ohlin-Vanek (HOV) predictions on the factor content of trade has already incorporated productivity differences across countries, the literature on output and endowments has mostly ignored them.[3] We show that the failure to account for these differences introduces a bias in the estimation of the relationship between output and endowments. Second, we take on board the insight of the growth literature that technology differences affect factor accumulation. As a result, factor endowments are not independent of productivity differences. When we take this into account, we can show that the bias is likely to be systematic.

We deal with this bias by integrating technology differences into the standard Heckscher-Ohlin type framework, and estimating the effect of endowments on output. To preview, our results bring us a considerable way towards resolving the puzzle: when productivity differences are controlled for, capital turns out not to be an important determinant of the pattern of specialization. We try to interpret these new results in the light of theories of specialization and capital mobility. We cannot prove that capital mobility is behind our result that capital is not an important determinant of the pattern of specialization. However, we think that capital mobility is a plausible explanation.

The outline of the paper is as follows: In Section 2, we use data on OECD countries to reproduce the result that when output is regressed on endowments, capital appears to be an important determinant of the pattern of specialization, while skilled and unskilled labor do not. Doing this demonstrates that the results in the second half of the paper are not dependent on differences between our data and the data used by previous work in the field. In Section 3, we outline evidence from other researchers that productivity differences across countries are empirically important. Our own data also suggest that productivity differences are large even across our sample of OECD

[2]See, for example, Katz and Murphy (1992), Lawrence and Slaughter (1993), Leamer (1994), Sachs and Shatz (1994), Wood (1994) and Davis (1998).

[3]Harrigan (1997) and Harrigan and Zakrajšek (2000) are exceptions. They allow for both productivity differences and endowments to determine the pattern of specialization.

countries. We explain how productivity differences can be integrated into the framework used by previous work. We show explicitly that if productivity differences are important, and they are not taken into account, the estimated coefficients in the regression of output on endowments will be biased. We show that with the additional assumption of Hicks-neutrality, we can sign the bias. As a baseline, we calculate Hicks-neutral productivities for the countries in our sample. We use these to control for productivity in regressing output on endowments, and find that capital is not significant while skilled and unskilled labor are. We discuss the impact of capital mobility on the pattern of specialization under various different assumptions. In Section 4, we perform some robustness checks on our results. These tests do not alter our result or our conclusions. The final section provides some concluding remarks, and outlines our plans for future work to test more carefully the role of capital mobility in the determination of production structure.

2 Benchmark Estimates

In this section, we motivate and estimate a model of the relationship between output and endowments very similar to that estimated by other researchers. We reproduce their results. This serves as an introduction to the literature. It also makes clear that the contrasting results we will present in the next section are not an artefact of our data.

2.1 The Model

We now describe a model which suggests a linear relationship between output and endowments. The assumptions necessary for linearity are strong. We are quite certain that these assumptions are not fully satisfied in the real world. But along with all the other researchers who have estimated a linear relationship between output and endowments, we work on the basis that linearity is a good approximation to the true relationship. Since the purpose of this section is merely to reproduce the results of other researchers, we will not test for linearity. When we estimate our preferred specification in the second part of the paper, we will test the linearity assumption.

Suppose that gross output of sector j in country c, y_j^c, can be written as a 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. The unit cost minimization problem for producers in sector j can then be written as:

$$\underset{\widetilde{\mathbf{v}}_j^c, \mathbf{m}_j^c}{\mathrm{Min}} \;\; \widetilde{\mathbf{w}}^c \widetilde{\mathbf{v}}_j^c + \mathbf{p}^c \mathbf{m}_j^c \text{ s.t. } f_j^c\left(\widetilde{\mathbf{v}}_j^c, \mathbf{m}_j^c\right) = 1 \tag{2}$$

where $\widetilde{\mathbf{w}}^c$ is the vector of factor prices and $\mathbf{p}^c$ is the vector of intermediate goods prices.[4] The first order conditions for the problem are:

$$\begin{aligned}
\widetilde{\mathbf{w}}^c &= \lambda^c \frac{\partial f_j^c\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right)}{\partial \widetilde{\mathbf{v}}_j^c} \\
\mathbf{p}^c &= \lambda^c \frac{\partial f_j^c\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right)}{\partial \mathbf{m}_j^c} \\
1 &= f_j^c\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right)
\end{aligned}$$

where λ^c is the marginal cost of production, equal to the price of sector j's output under perfect competition. Now, suppose that technology is identical in all countries ($f_j^c = f_j$), the law of one price holds for goods prices ($\mathbf{p}^c = \mathbf{p}$), and factor endowments are such that there is factor price equalization ($\widetilde{\mathbf{w}}^c = \mathbf{w}$). The law of one price for goods prices and factor price equalization together imply that $\lambda^c = \lambda$. Then, for all countries:

$$\mathbf{w} = \lambda \frac{\partial f_j\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right)}{\partial \widetilde{\mathbf{v}}_j^c} \tag{3}$$

$$\mathbf{p} = \lambda \frac{\partial f_j\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right)}{\partial \mathbf{m}_j^c} \tag{4}$$

$$1 = f_j\left(\widetilde{\mathbf{v}}_j^{c*}, \mathbf{m}_j^{c*}\right) \tag{5}$$

In order for all of these equalities to hold for every country, we must have $\widetilde{\mathbf{v}}_j^{c*} = \widetilde{\mathbf{v}}_j^*$ and $\mathbf{m}_j^{c*} = \mathbf{m}_j^*$ for all countries c. That is, the unit factor input requirements and the unit intermediate input requirements must be the same across countries. Denote $\widetilde{b}_{fj} = \widetilde{\mathbf{v}}_{fj}^*$ the unit input requirement of factor f in sector j. We use these to form 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 then requires that

$$\widetilde{B}\mathbf{y}^c = \widetilde{\mathbf{v}}^c \tag{6}$$

holds 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. In the case where there are the same number of goods and factors ($F = J$), $\widetilde{B}$ will be invertible. Let $\widetilde{B}^{-1} = R$. Then we have

$$\mathbf{y}^c = R\widetilde{\mathbf{v}}^c \tag{7}$$

[4] For the moment, let $\widetilde{\mathbf{v}}_j^c$ indicate the vector of measured factor endowments, and $\widetilde{\mathbf{w}}^c$ the corresponding vector of factor prices.

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.[5] These are known as Rybczynski equations.[6] We now run exactly these regressions.

2.2 Estimation

2.2.1 Data description

Here, we give a brief description of the data we use. The details are in Appendix A. For 21 OECD countries, we have data on GDP, gross output in 25 3-digit ISIC manufacturing sectors, capital stock, skilled and unskilled labor, and arable land, all in 1988. GDP is from the OECD. Sectoral output is from UNIDO. Capital stock and total labor force are from the Penn World Tables. Arable land is from FAO.

We restrict ourselves to 21 OECD countries because many of the assumptions of our model, such as FPE and the absence of trade costs, are more reasonable for the OECD than they are for a larger sample.[7]

The theory of Rybczynski equations applies to both sectoral gross output and sectoral value added. For two reasons, we prefer to work with gross output as our baseline. First, we think that the gross output data is of better quality than the value added data. Second, other researchers in the field use gross output, and we would like our work to be comparable with theirs. We will run some regressions using value added as a robustness check.

Sectoral output and GDP are converted into dollars using the average yearly market exchange rate for 1988 from IFS. This conversion implicitly assumes that the law of one price holds for manufacturing output, an assumption needed for FPE. In converting this way, we also follow the convention in the trade literature.[8]

[5] Given the unit input requirements of both direct factors and intermediate inputs, value added becomes a fixed proportion of gross output in each sector. This implies that (6) also holds when y^c is the vector of sectoral value added instead of output. Therefore sectoral value added is also a linear function of endowments. The rows of $\tilde{B}$ have only to be scaled by the ratio of gross output to value added in each sector.

[6] In a world with multiple cones of specialization, the theory we have outlined applies within each cone.

[7] Our 21 countries are: Australia (AUS), Austria (AUT), Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom, and the United States. They are all members of the OECD in 1988. Iceland and Luxemburg are excluded from the sample because of their size. Switzerland is excluded because sectoral production data is incomplete.

[8] Note, however, that the 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.

Out of a possible 28 3-digit manufacturing sectors, we use only 25. We exclude one sector because it is a residual category, including everything not counted elsewhere. We exclude also Petroleum refineries and Miscellaneous petroleum and coal products. We do this for three reasons. First, we do not include factors relevant to these sectors in our data set. Second, for many countries, data on these sectors are not reported. Third, some countries report output to UNIDO at producer prices, while others report it at factor value. Distortions of output figures due to cross-country differences in taxation can be large in these generally heavily taxed sectors, leading to problems of comparability across countries.[9]

The capital stock we use is the sum of producer durables and nonresidential construction. In the Penn World Tables, each of these series is constructed from the relevant annual investment series using an appropriate depreciation rate. We exclude residential construction from our baseline measure because, as suggested by Harrigan (1997), in this context, residential construction can be better interpreted as consumption rather than as investment in the capital stock. Again, we will run some regressions using an all-inclusive measure of capital for robustness.

The labor force is broken down into skilled and unskilled labor using data from the OECD publication Education at a Glance on the educational attainment of the employed population. Workers who have a senior cycle second level education or more are considered "skilled". The standard in the literature is to use the Barro-Lee data set to obtain this decomposition. We believe that for OECD countries, the OECD education data is more reliable.[10]

2.2.2 Econometric issues

The model we outline above suggests for each sector a cross-country linear regression of sectoral output on factor endowments. That is, for every sector j, we would estimate:

$$y_j^c = r_{j0} + r_{j1}v_1^c + \ldots + r_{jF}v_F^c + \epsilon_j^c, \tag{8}$$

or, in matrix notation,

$$\mathbf{y}_j = V\mathbf{r}_j + \epsilon_j. \tag{9}$$

We include a constant term in the regression to pick up the effect of omitted factors.[11] The error term ϵ_j^c captures both shocks to sectoral production and the deviation of the country-c endowment of omitted factors from the cross-country mean. In order for the estimated coefficients to be unbiased,

[9] This is probably true also for the Beverages and Tobacco sectors.

[10] 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.

[11] The coefficient r_{j0} will be a weighted sum of the cross-country average endowments of the omitted factors, where the weights are the Rybczynski coefficients on those factors.

it must be assumed that the error term ϵ_j^c is uncorrelated with the measured factor endowment of country c, that is with the factors included in V. We will come back to this assumption later in the paper.

There is likely to be a problem of heteroskedasticity in the estimation of (9). We expect the variance of the error term to be strongly correlated with country size. The previous literature has dealt with this issue by weighting the observations by either GDP or its square root.[12] Weighting by GDP has a nice interpretation, as the regression then becomes one of shares in total output on measures of factor abundance. This method of correcting for heteroskedasticity is strictly correct only if GDP is independent of the error term. We know that GDP is the sum of value added over all sectors, and thus depends on the error term in each sector. So strictly speaking, it is not independent of the error term. If shocks to production are not correlated across sectors within countries, the problem could be solved by using $\left(GDP^c - y_j^c\right)$ as weights. If shocks to production are correlated across sectors within countries, we could weight instead by one factor or a linear combination of factors. As it turns out, our manufacturing sectors are individually small relative to GDP. And when we perform the regression weighting by total labour force rather than GDP, the pattern of results are essentially unaffected. So we feel justified in keeping GDP as our baseline weight, in accordance with the previous literature.[13]

For each sector our baseline equation is then:

$$\frac{y_j^c}{GDP^c} = r_{j0}\frac{1}{GDP^c} + \sum_{f=1}^{F} r_{jf}\frac{v_f^c}{GDP^c} + \varepsilon_j^c. \tag{10}$$

We will want to test cross-equation restrictions on coefficients, for example, the restriction that capital does not matter for the production structure. In order to test these restrictions, we treat the set of equations as a seemingly unrelated regressions problem. When we do this, we correct for heteroskedasticity driven by industry size. That is, we assume that the variance of the error term is proportional to the square root of the total sample output of the sector in question.[14]

[12] The problem with using endogenous heteroskedasticity correction is that the results are driven by a big outlier in size: the US. See Reeve (1998) for a detailed explanation.

[13] We also estimate using the square root of GDP as weights, and the results do not change much.

[14] This procedure can be thought of as a simplified SUR where we assume that all the off-diagonal terms are zero, i.e., errors are not correlated across equations. This assumption may seem strong. However, under the assumption that there are no technology differences, we do not have any prior on the particular structure of correlations between errors. A natural restriction would be to impose that errors in all sectors of a particular country sum up to zero, but we cannot do that since we are only using manufacturing sectors.

2.2.3 Results

The results from estimating (8) are reported in Table 1. We draw particular attention to the coefficient on capital. It is positive in all but one sector. In 15 out of 25 sectors it is significantly positive. The coefficient on skilled labor is negative for some sectors, positive for others. It is significantly different from zero in only 5 sectors. The coefficient on unskilled labor is also negative for some sectors, positive for others. It is significantly different from zero in 8 sectors. The coefficient on land is negative in all but two sectors. We do not report R^2s for the equations because the weighted regression does not include a constant term. Where there is no constant term, the R^2 is meaningless. Instead, we report the average prediction error (APE), for each equation, and for the system as a whole.[15] The APE for our system is 61%, similar to that obtained by others who have estimated these equations.

We estimate a number of variations on our baseline equation. First, we use value added rather than gross output as the dependent variable. Second, we use total capital rather than non-residential capital as our dependent variable. Third, we estimate without a constant term. Fourth, we use the square root of GDP rather than GDP as our weighting factor. Fifth, we weight using total labor rather than GDP. The results are in Appendix C, available on request. In all of these variations, the results are roughly similar: the coefficient on capital is almost always positive, and frequently significantly positive. The coefficients on the other factors are neither uniformly positive nor uniformly negative, and they are much less frequently significantly different from zero.

Our results are very similar to those obtained by other researchers using samples of OECD countries, principally, Harrigan (1995), Davis and Weinstein (1998a), Bernstein and Weinstein (1998), and Reeve (1998). They get coefficients on capital which are almost always positive, and frequently significantly positive. Increases in the capital stock are also associated with increases in the production of most manufacturing sectors in Leamer (1987) and Schott (1999), who work with larger samples of countries, and do not assume a uni-cone model.[16] Most of these researchers interpret their results as an indication that capital is an important determinant of the pattern of specialization.

A point that has been a source of some confusion in previous literature is that a positive

[15] 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 all observations.

[16] Leamer (1987) approximates the multicone model by regressing y_j/L on a quadratic function of the capital/labor ratio. For almost all sectors, he finds an inverted U-shaped relationship, but "the estimated function is also virtually linear over the relevant range". Schott (1999) divides his sample of 45 countries into 4 different cones, one of which includes 36 countries. Within this cone - the only one with degrees of freedom enough to make the estimates reliable - he finds the coefficient on capital positive in all sectors.

Rybczynski coefficient on a factor in a given sector does not necessarily mean that the factor is a source of comparative advantage in that sector. A factor should be properly thought of as a source of comparative advantage in a sector only if an increase in the total endowment of the factor leads a country to export more of the output of that sector. This effect is captured by the sign of the coefficients from a regression of trade on factor endowments, not output on factor endowments. A positive Rybczynski coefficient merely indicates that when the factor endowment increases, more is produced. Exports depend also on how much more is consumed. If one is willing to assume that preferences are homothetic, then the coefficients of both regressions are related by:[17]

$$\beta_{jf} = r_{jf} - \frac{Y_j^w}{Y^w} w_f \tag{11}$$

where β_{jf} is the coefficient on factor f from a trade regression, r_{jf} is the Rybczynski coefficient, Y_j^w is the world production of sector j, Y^w is total world output, and w_f is the return to factor f, common across countries by assumption. We make a rough attempt to measure comparative advantage by calculating β_{jf} as in (11). To do this, we use the returns to factors in the US (assumed identical in every country by FPE), and sectoral shares of world production from UNIDO data on more than 60 countries. The calculated βs are in Table 2. This table indicates that capital is indeed a source of comparative advantage in most manufacturing industries. However, the proportional model of the consumption side is primitive, and we are not able to attach significance levels to the comparative advantage coefficients produced. As a result, we do not put too much weight on this exercise, and show it only for illustrative purposes.

As we explained in the introduction, we find both our results and the results of previous work puzzling. It is not obvious to us that the Rybczynski coefficient on capital should be positive in almost all manufacturing sectors. Further, skilled and unskilled labor appear to be much less important than capital as determinants of the pattern of specialization.[18] This goes against our priors. It also goes against the priors of many other researchers who focus on skilled and unskilled labor as determinants of trade patterns. But there are important problems with the Rybczynski estimation we have just performed. We will now show that productivity differences across countries are empirically important. We will show that failure to control for these differences in the estimation we have just performed leads to biased results. When productivity differences are taken into

[17] See Leamer (1984) for a demonstration.

[18] We test the linear restrictions that each factor individually can be excluded from the system of equations. Our test is performed on a model which corrects for sectoral heteroskedasticity as well as country heteroskedasticity. The F-statistic for the restriction that capital does not matter is 4.11. The F-statistic for the restriction that skilled labor does not matter is 1.60. The F-statistic for the restriction that unskilled labour does not matter is 2.88. The F-statistic for the restriction that land does not matter is 1.99. The critical values are 1.82 and 1.53 at the 1% and 5% significance levels respectively.

account, the results will look quite different.

3 Introducing productivity differences

3.1 Evidence

One of the strongest assumptions of the Heckscher-Ohlin model is that technology is identical across countries. In this section, we outline evidence that this is not a good approximation. A large body of research in the growth literature has focused on this assumption during the last decade. The main concern of this research has been to determine whether factors alone can explain the large observed differences in per-capita income accross countries, or whether technology differences are also necessary. This is obviously relevant to the question of whether endowments alone can explain the pattern of specialization. Mankiw, Romer and Weil (1992) argue that the Solow model, augmented to include human capital, can account for most of the variation in per capita income across countries. This would imply that there is no need to relax the assumption of identical technologies. However, the literature spawned by this paper has generally concluded the opposite: technology differences are important in explaining per-capita income differences. Islam (1995, 1999), Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) find that productivity differences across countries are empirically large, and important in explaining income differences, even for OECD countries. For example, Islam (1999) finds that the US has TFP three times that of Turkey.

Conrad and Jorgenson (1995) and Dougherty and Jorgenson (1999) use a methodology that disaggregates factors into much narrower categories than the literature we have just referred to. They use very detailed information on quantity and quality of these factors in the most advanced developed countries to calculate productivity differences between them. They find that productivity differences are non-trivial even for these countries. Hendricks (1999) provides evidence of the existence of productivity differences from a very different perspective. He shows that the increase in earnings of immigrants to the US cannot be accounted for by differences in factor endowments between their country of origin and the US.

The trade literature also provides evidence of the importance of productivity differences across countries. Within the context of the Heckscher-Ohlin-Vanek (HOV) theory, both Trefler (1995) and Davis and Weinstein (1998b) find that productivity differences are necessary for the predicted and actual factor content of trade to be close. One of the striking facts in Trefler (1995) is the finding of the "endowments paradox". The paradox is that rich countries tend to be scarce in most factors, and poor countries tend to be abundant in all factors. This paradox is present in our sample, even though it includes only OECD countries, for which we might expect productivity differences to be small. Table 3 shows factor abundance as conventionally measured[19] for each factor and country in our sample. The most striking cases are those of Sweden, which appears to be scarce in all factors, and Australia, Greece, New Zealand, and Turkey which appear to be abundant in all factors. The case of Turkey is particularly noteworthy, because it appears to be the country most abundant in each one of the four factors.

The endowments paradox is important not only because it illustrates neatly the need to account for productivity differences. It is also at the heart of the estimation of Rybczynski equations. It can be seen in (10) that the weighted equation is essentially a regression of sectoral shares on these measures of factor abundance (scaled up by the common denominator V_f^w/GDP^w). As a result, the endowments paradox is likely to have an important effect on the regression results.

To conclude this section, differences in technology across countries are empirically important. We will now show how they may be introduced into the Rybczynski framework. We will show that if they are not accounted for, the estimated coefficients will be biased.

3.2 Productivity differences and estimation bias

3.2.1 Model

Suppose that differences in technology across countries can be represented as factor-specific productivity differences.[20] So one unit of factor f in country c is equivalent to a_f^c units of that factor in a numeraire country. If factor f in country c is very productive relative to the numeraire, we will have $a_f^c > 1$, if it is not very productive relative to the numeraire, we will have $a_f^c < 1$. We will now interpret all the variables with tildes in Section 2.1 as factor endowments measured in efficiency units. We can then write $\tilde{\mathbf{v}}_j^c = A^c \mathbf{v}_j^c$, 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. Now $\tilde{\mathbf{w}}^c$ is the vector of factor returns to efficiency units of factors.

Assume again 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

[19] The measure of factor abundance is $\left(v_f^c/GDP^c\right) / \left(v_f^w/GDP^w\right)$, where the superscript w denotes the world (i.e., all the countries in the sample). A value greater than one implies relative abundance of the factor.

[20] This is not the most general representation of technology differences. For example, productivity of a given factor in a given country could be allowed to differ across sectors. But we think that factor-specific differences are sufficiently general for our purposes.

factor price equalization holds. That is, factor rewards to efficiency units of factors are equalized across countries: $\widetilde{\mathrm{w}}^c = \mathrm{w}$.[21] The solution to problem (2) is then exactly as in Section 2.1:

$$\mathrm{w} = \lambda \frac{\partial f_j \left(\widetilde{\mathrm{v}}_j^{c*}, \mathrm{m}_j^{c*} \right)}{\partial \widetilde{\mathrm{v}}_j^c} \tag{12}$$

$$\mathrm{p} = \lambda \frac{\partial f_j \left(\widetilde{\mathrm{v}}_j^{c*}, \mathrm{m}_j^{c*} \right)}{\partial \mathrm{m}_j^c} \tag{13}$$

$$1 = f_j \left(\widetilde{\mathrm{v}}_j^{c*}, \mathrm{m}_j^{c*} \right) \tag{14}$$

Again, in order for all of these equalities to hold for every country, we must have $\widetilde{\mathrm{v}}_j^{c*} = \widetilde{\mathrm{v}}_j^*$ and $\mathrm{m}_j^{c*} = \mathrm{m}_j^*$ for all countries c. That is, efficiency-equivalent unit input requirements for each industry will be the same across countries. These $\widetilde{b}_{fj}$ can be used to form $\widetilde{B}$, the unit direct efficiency-equivalent factor input requirement matrix. This is common to all countries. Under the assumption that it can be inverted (i.e. that there are the same number of goods and factors), with $\widetilde{B}^{-1} = R$, we have a linear relationship between output and efficiency-equivalent factors:

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

We can estimate this relationship by regressing output on efficiency-equivalent factors using cross-country data.

3.2.2 Estimation bias

We can now think about what happens when there are productivity differences across countries, but these are not controlled for. If there are productivity differences, assuming some iid error, the true model is:

$$y_j^c = \mathrm{v}_j^{c\prime} A^c r_j + \epsilon_j^c.$$

But we estimate instead:

$$y_j^c = \mathrm{v}_j^{c\prime} r_j + \theta_j^c.$$

Adding and subtracting, we can write:

$$y_j^c = \mathrm{v}_j^{c\prime} A^c r_j + \mathrm{v}_j^{c\prime} r_j - \mathrm{v}_j^{c\prime} r_j + \epsilon_j^c \tag{15}$$

$$y_j^c = \mathrm{v}_j^{c\prime} r_j + \mathrm{v}_j^{c\prime} \left(A^c - I \right) r_j + \epsilon_j^c \tag{16}$$

$$y_j^c = \mathrm{v}_j^{c\prime} r_j + \theta_j^c \tag{17}$$

[21] Note that $\mathrm{w}^c = A^c \widetilde{\mathrm{w}}^c = A^c \mathrm{w}$.

where $\theta_j^c = \mathrm{v}_j^{c\prime}\,(A^c - I)\,r_j + \epsilon_j^c$. The error term in this model is correlated with the independent variables (unless $A^c = I$ for all c). So if the model is estimated without controlling for productivity differences, the estimates of the R matrix will be biased.[22]

Hicks-neutral productivity differences are the particular case of factor-specific differences where the efficiency of all factors in country c relative to those in the numeraire country is the same. A single parameter a^c for each country characterizes productivity differences. Hicks-neutral technology differences are widely used in the growth literature to model cross-country technology differences. The trade literature tests Hicks-neutrality as a by-product of the literature on testing HOV. Trefler (1995) finds that a model augmented with Hicks-neutral technology differences does a better job of predicting the factor content of net exports than either the baseline model which assumes identical technologies, or models with more general technology differences. Davis and Weinstein (1998b) look at the fit from regressing the measured factor content of production on the factor content predicted by variants of the HOV model. For the production side, most of the improvement in fit between their baseline case and their preferred specification is obtained when Hicks-neutral efficiency shifts are introduced. We see this as evidence that Hicks-neutrality is a good first-order approximation to true differences in technology across countries. Further, they have the merit of simplicity. In what follows, we will work with the assumption of Hicks-neutral differences in technology as our baseline case. Later, we will work with factor-specific productivity differences as a robustness check.

Given the assumption of Hicks-neutrality, it is easy to show that the econometric bias we have just pointed out is likely to be systematic. The theoretical literature on economic growth predicts that more productive countries will accumulate more capital relative to their labor endowment than less productive countries.[23] This result is true both in closed economy exogenous growth models (such as the Solow and the Ramsay models) and for the typical closed economy endogenous growth model (the AK model).[24] The open-economy case is treated by Ventura (1997), who studies the dynamics of accumulation under conditional FPE. He finds that the sign of the correlation between productivity and the K/L ratio across countries depends on the elasticity of substitution between factors. However, for the case consistent with the finding of conditional convergence ($\sigma > 1$), the K/L ratio is proportional to the productivity parameter in the steady state.

The positive association between the level of technology and the K/L ratio is also empirically strong. Klenow and Rodriguez-Clare (1997) find a strong positive correlation between these two variables, as do Hall and Jones (1999). As we will see later, this result also holds in our OECD

[22] Estimated standard errors are also biased.

[23] This connection has not so far been confronted by the empirical literature on specialization and endowments, which takes the latter as exogenously given.

[24] See Barro and Sala-i-Martin (1995) for a textbook review.

sample.

When technology differences are Hicks-neutral, equation (16) can be rewritten as:

$$y_j^c = \mathbf{v}_j^{c\prime} r_j + (a^c - 1)\,\mathbf{v}_j^{c\prime} r_j + \epsilon_j^c \tag{18}$$

where the error term is $\theta_j^c = (a^c - 1)\,\mathbf{v}_j^{c\prime} r_j + \epsilon_j^c$. It is clear that other things equal, the error term will tend to be large for more productive countries (large a^c), and small for less productive countries (small a^c). Now let us think about what happens if productivity differences across countries are serially correlated.[25] For productive countries, the error term θ_j^c will tend to be positive and large because $a^c > 1$. Given the serial correlation of productivity, and the impact of productivity on incentives for capital accumulation, these countries will tend to be relatively capital abundant. The opposite is true for less productive countries. The positive correlation between the error term and capital will bias upwards the estimated coefficient on capital. We think this bias is the driving force behind the result of the previous literature that the coefficient on capital is positive and significant in most manufacturing sectors.[26]

If skilled labor also accumulates in response to market incentives, there should be a similar upward bias of the coefficient on skilled labor. In fact, market incentives have a much weaker effect on skilled labor accumulation than on physical capital accumulation. Also, "time to build" is likely to be longer for skilled labor than physical capital. As a result, we do not expect the bias on the coefficient on skilled labor to be so strong.

There are three pieces of evidence suggestive of the fact that this bias on the coefficient on capital is important. First, Bernstein and Weinstein (1998) estimate equation (8) not only for a sample of OECD countries, but also for Japanese regions. In the case of Japan, (in contrast to the OECD) the coefficient on capital turns out not to be positive and significant in most manufacturing sectors. This could be explained by the fact that technology differences across Japanese regions are small, and hence the bias is small.

[25] We believe that in levels, this is indeed the case.

[26] Harrigan (1995) gets positive and significant coefficients on capital even in a specification where he runs this regression on a panel with fixed effects. In this case, parameter identification comes from within-country variation, so the argument we have just made about capital and productivity being correlated across countries does not apply. But we can make a similar argument in a business cycle context. In that case, productivity is determined by capacity utilization, which enters in the same form as the a^c above. During an expansion, factors are working at or near full capacity, so output will be high relative to measured endowments. At the same time, investment is also high. Since Harrigan uses a depreciation rate of 13.3% (as is common in the trade literature), the capital stock will be quite sensitive to the investment rate. Thus, it will be more correlated with the business cycle than other factors. So again, we have a positive correlation between productivity and the measured capital stock, which may lead to the estimated coefficient on capital being biased upwards from the true Rybczynski coefficient.

Second, Harrigan (1997) and Harrigan and Zakrajšek (2000) examine the role of factors as determinants of production using an approach different from the rest of the literature. Their estimation is based on assuming a translog revenue function, and using mainly within-country variation in a panel to identify the parameters. Their specification implicitly allows for productivity differences.[27] They do not find the coefficient on capital positive and significant in most manufacturing sectors.

Third, Turkey is an outlier in our sample in terms of productivity. When we exclude it from our estimation (see Table 4), the strong pattern of a positive and significant coefficient on capital is attenuated. In an earlier version of this paper, we used a sample of 60 countries, for which productivity differences are obviously more extreme than for our current OECD sample. Using the larger sample, the coefficient on capital was positive and very strongly significant in every sector.

We now describe the construction of productivities and the estimation of the adjusted model.

3.3 Estimation

3.3.1 Data description and construction of TFP

Our basic data is exactly as described in Section 2.2.1. But now, we need a measure of TFP (or a^c) for each country in order to obtain efficiency-equivalent factor endowments. TFP indices have a dual role. First, they capture the true contribution of "productivity". Second, they capture the contribution to production of unobserved factors and measurement error in observed factors. Hence they are sensitive to the factors included in the calculation, how they are measured, and the assumed functional relationship between factors and production. So we need a TFP measure consistent with our factors. We also want our baseline measure of TFP to be consistent with our null hypothesis of conditional factor price equalization.[28]

Conditional factor price equalization and Hicks-neutrality 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 prices, the revenue function is linear in factor endowments. Hence

$$\begin{aligned} GDP^c &= \sum_{f=1}^{F} v_f^c w_f^c \\ &= a^c \sum_{f=1}^{F} v_f^c w_f^{US} \end{aligned}$$

[27] Harrigan (1997) calculates sectoral TFPs for every country. Harrigan and Zakrajšek (2000) do not do this explicitly.

[28] The available calculations of TFP we are aware of do not satisfy these requirements.

If we know the factor returns in the US, we can estimate a^c as

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

To estimate TFP in this way, we need data on GDP and factor endowments, which we already have. We estimate factor returns for the US by dividing total factor income for each factor in 1988 by the relevant factor endowment. The sources and construction of total factor income for our factors are described in Appendix A and Appendix B. We report the FPE-consistent measure of TFP in Table 5, together with the implied ranking of countries. This table reports other productivity measures which we will explain later. The coefficients of variation of the productivity measures, and the matrix of correlations are also provided.

We can use our TFP estimates to construct efficiency-equivalent measures of factor abundance.[29] By construction, the endowments paradox is not present in these measures. In Table 6, we give the correlation between our measure of TFP and these measures of factor abundance. In accordance with the theoretical prediction, the correlation between productivity and capital abundance is 0.83.

3.3.2 Econometric issues

Under the assumption of Hicks-neutrality, Section 3.2.1 suggests the following specification, analagous to (8):

$$y_j^c = r_{j0} + r_{j1} a^c v_1^c + \ldots + r_{jF} a^c v_F^c + \epsilon_j^c \tag{19}$$

where the $a^c v_f^c$ are efficiency-equivalent factor endowments.[30] We construct the efficiency-equivalent factor endowments using the TFP estimates described in the previous section. As before, we include a constant term in the regression. We still have the problem that the variance of the error term is correlated with country size. So, once again, we weight observations by GDP and estimate as our baseline:

$$\frac{y_j^c}{GDP^c} = r_{j0}\frac{1}{GDP^c} + \sum_{f=1}^{F} r_{jf}\frac{a^c v_f^c}{GDP^c} + \varepsilon_j^c. \tag{20}$$

For the purposes of joint tests of factor exclusion restrictions, we estimate a model which is identical to the above, except that we weight additionally by the square root of sector size as already described.

[29] The measure of factor abundance is now $\left(\tilde{v}_f^c/GDP^c\right) / \left(\tilde{v}_f^w/GDP^w\right)$.

[30] We could estimate the a^c and the r_{jf} jointly using non-linear methods. We tried this, but we had difficulty finding a global minimum for the objective function. In any case, given the small number of observations relative to the number of estimated parameters, the joint estimation probably asks too much of the data.

3.3.3 Results

Table 7 gives the results from estimating equation (20) using the FPE-consistent measure of TFP to construct efficiency-equivalent factor endowments. There are two main points to note. First, the coefficient on capital is no longer uniformly positive, and it is significant in only one sector out of 25. Second, the coefficient on skilled labor is significantly different from zero in 17 sectors, and the coefficient on unskilled labor is significantly different from zero in 14 sectors. The coefficient on arable land is negative in most sectors, but significant in only a few, a result which is not surprising for manufacturing sectors. We report the APE for each equation and for the system as a whole. The overall APE is 54%, lower than it was for the unadjusted model.

As in the case of the model with unadjusted factors, we estimate some variations on the basic specification. We exclude Turkey, and in contrast to the case of the unadjusted model, the results do not change. We also use value added rather than output as the dependent variable. We use different measures of capital. We estimate without a constant. We correct for heteroskedasticity using the square root of GDP, and then total labor, instead of GDP. The results of all of these variations are in Appendix C, available on request. None of these corrections affects the basic pattern of results.

The results in Table 7 contrast strongly with those obtained in the unadjusted model. Where before, capital was positive in all but one case, now it is positive in some sectors and negative in others. Before, it was often significantly positive. Now it is significant in only one sector. Given our prediction of the direction of the bias on capital, this is exactly what we expect. Further, the coefficients on skilled and unskilled labor are significantly different from zero in many more sectors than before.

The fact that the coefficient on capital is significantly different from zero in only one sector implies that capital is not an important determinant of the pattern of specialization in the OECD. Conversely, the fact that the coefficients on skilled and unskilled labor are frequently significantly different from zero implies that these factors are important determinants of the pattern of specialization in the OECD. We test the joint restriction that capital can be excluded from the regressions for all sectors. We cannot reject this restriction at the 5% level of significance. We can reject the restriction that skilled labor can be excluded, and the restriction that unskilled labor can be excluded, both at the 1% level of significance.[31] This is confirmation that skilled and unskilled labor, not capital, are important determinants of the pattern of specialization in the OECD.

[31] The F-statistic for the restriction that capital can be excluded is 1.23. The F-statistic for the restriction that skilled labor can be excluded is 3.57. The F-statistic for the restriction that unskilled labor can be excluded is 5.44. The F-statistic for the restriction that land can be excluded is 1.02. The critical values are 1.82 and 1.53 at the 1% and 5% significance levels respectively.

We now examine our coefficient estimates more closely to see whether they are sensible. As before, we can do a rough check on whether our factors are sources of comparative advantage by subtracting the return-weighted consumption share for each sector. The results are reported in Table 8. Again, we do not attach too much weight to this table, but the sectoral pattern of comparative advantage it suggests seems broadly reasonable. Skilled labor appears to be a source of comparative advantage in Printing and Publishing, the Machinery sectors, Transport Equipment and Professional and Scientific Equipment. It is a source of comparative disadvantage in Leather Products and Footwear. Unskilled labor is a source of comparative advantage in Textiles, Wearing Apparel and Footwear and a source of comparative disadvantage in the Machinery sectors, Transport Equipment and Professional and Scientific Equipment. We interpret the table as an indication that the coefficients we have estimated for the production side are sensible.

A relevant experiment for policy purposes is to examine how the production structure would change if unskilled workers become skilled, as would happen if there were educational upgrading within a country. The difference between the coefficient on skilled labor and the coefficient on unskilled labor gives the sign of the effect on the production structure. Table 9 shows these differences, together with the significance level of the test of the restriction that both coefficients are equal. The pattern of signs is quite reasonable. For example, shifting from unskilled to skilled tends to decrease output of Leather Products and Footwear. The same shift tends to increase output of Printing and Publishing, the Machinery sectors and Professional and Scientific Equipment. This shows that positive coefficients on both skilled and unskilled labor can be reconciled with our intuition about input intensities in different sectors.

We can calculate for each sector the elasticity of sectoral output with respect to a change in measured factor endowment:

$$\begin{aligned} \text{elasticity} &= \frac{\partial y_j}{\partial v_f} \overline{\left(\frac{v_f}{y_j}\right)} \\ &= r_{jf} \overline{\left(\frac{v_f}{y_j}\right)} \end{aligned}$$

where $\overline{\left(\frac{v_f}{y_j}\right)}$ is the cross-country mean of the factor-to-sectoral-output ratio. These elasticities are reported in Table 10.[32] Their magnitudes are not wildly out of line with our priors, suggesting that the magnitudes of our coefficient estimates are reasonable.

[32]These elasticities are similar in spirit to the beta coefficients proposed by Leamer (1984). In this case, we think that elasticities evaluated at the cross-country mean of the factor-sectoral output ratio have a more intuitive interpretation. The factor-sectoral output ratio does not depend on country size. Given the wide variation in country size, it is not obvious to us that increasing factor endowments by the cross-country standard deviation of factor endowments is a relevant experiment.

Lastly, we can compare our results with those of Harrigan and Zakrajšek (2000)[33], who follow a different approach from that of the rest of the literature. They derive their estimating equations from a translog revenue function. The translog function, although quite general, does not nest the linear revenue function obtained under the assumption of FPE. In effect, they regress shares of sectoral value added on the log of factor endowments, imposing the restriction that the sum of coefficients is equal to 0 (an implication of constant returns to scale under their assumptions). They also include country fixed effects and time trends, and run a fixed effects and a random effects model on a panel of 28 countries (including non-OECD countries) over the period 1970-1992. We do not agree with this approach, mainly because the assumption that the parameters to be identified are stable over a period of 23 years seems very strong to us. Their results are not as stark as ours, but they also find in both the fixed effects and random effects estimation that the coefficients on skilled and unskilled labor are more often significant that the coefficient on capital.

To summarize, taking account of Hicks-neutral productivity differences, the estimated model suggests that skilled and unskilled labor, not capital are important determinants of the pattern of specialization. The estimated coefficients are reasonable along other dimensions, which convinces us that our main result is worth looking into. In the next section, we will test the robustness of the main result. Meanwhile, we will discuss how we interpret our result in terms of capital mobility.

3.4 Capital mobility as an explanation

As a first pass, capital mobility appears to be a plausible explanation for the fact that the coefficient on capital is not significant in our adjusted model. We believe that this is indeed the case. Capital mobility is likely to be at the root of our results, but the correspondence between theory and empirics is less than clear-cut as we will now describe. First, we assume perfect capital mobility, and discuss the case where FPE holds, and the case where FPE does not hold. Second, we discuss imperfect capital mobility.

Whether FPE holds or not, if capital is perfectly mobile, immobile factors alone determine the structure of production in each country.[34] Capital moves across countries in order to satisfy the input requirements given by the predetermined production structure. This in turn determines the total amount of capital in a country. Therefore, if capital is perfectly mobile, it should not be included in a regression of output on endowments, since it adds no information about the structure of production.[35] In a properly specified model of the relationship between output and endowments,

[33]Harrigan (1997) divides capital between Producer durables and Non-residential construction, making his results difficult to compare with the rest of the literature.

[34]See Leamer (1984) and Wood (1994) for details.

[35]This argument is distinct from the argument on capital accumulation made earlier. If capital accumulation is

we should not be able to reject the restriction that capital can be excluded, both for each equation individually, and for the system as a whole.

Let us consider first the case of perfect capital mobility in a world with FPE and no technology differences. If there are an equal number of goods and immobile factors, we will have for each industry j the linear relationship

$$\mathbf{y}_j = V\mathbf{r}_j$$

between output and the matrix of endowments of immobile factors V. As an accounting identity, the capital endowment of each country can be written as a linear function of the outputs of each sector, where the coefficients are the unit capital requirements in each sector:

$$K^c = \sum_{j=1}^{J} y_j^c a_j^k$$

But the outputs of each sector can be written as linear combinations of the immobile factors, so substituting, capital becomes a linear function of the immobile factors:

$$K^c = \sum_{j=1}^{J} V^c \mathbf{r}_j a_j^k$$

If this is the case, and we include capital in a regression of output on endowments, we will have perfect multicollinearity, and we will not be able to invert the $V'V$ matrix.[36] Of course, factor endowments are in fact measured with error, and there are also omitted factors. So even if the $V'V$ matrix can be inverted, it does not rule out perfect capital mobility. In this case, it is likely that the standard errors attached to all coefficients will be large, as the independent variables would still be strongly collinear.

The next case to consider is that of perfect capital mobility when FPE does not hold. For example, FPE could fail due to the existence of (even small) trade costs. In this case, the structure of production is still determined by immobile factors alone, so capital stock will not add anything to the explanation of production structure. But once we are out of FPE, the linear relationship between sectoral output and endowments no longer holds. Moreover, the (non-linear) function relating output to endowments is not necessarily the same across countries. The results of an estimation where linearity is assumed and capital is included will depend on how well this approximation

driven by technology differences, non-acummulable factors and technology alone (and not the accumulable factor) drive the pattern of specialization *in the long run*. However, if capital is accumulable but immobile, the structure of production at any point in time will still depend on total capital at that point in time. Capital should therefore be included in a cross-country regression of output on endowments.

[36]We thank Fernando Broner for pointing this out.

works. There is no guarantee that capital will turn out not significant even if it is perfectly mobile, although we think capital is unlikely to be significant in this case.

We now discuss imperfect capital mobility. Perfect capital mobility is in fact inconsistent with our assumption of conditional FPE. In an equilibrium where conditional FPE holds, returns to efficiency units of capital are equalized across countries, but returns to natural units are not. They are proportional to productivity. There are then incentives for capital to flow from less to more productive countries until returns to natural units are equalized. But at this point, conditional FPE will no longer hold.[37] Of course, we know that capital is not perfectly mobile. The problem is then how to model partial capital mobility. There are many explanations of imperfect capital mobility, but we are unaware of any attempt to match them with a general equilibrium trade model. All we know is that partial mobility of capital should reduce dispersion in returns to natural units across countries, though it may not be enough to equalize them. As a result, with partial capital mobility, we would expect the returns to capital across countries to be less dispersed than the returns to other factors. This is in fact what we see in the data. But we still do not have a well-formulated theory of imperfect capital mobility that clearly predicts our results.

To sum up, we cannot claim that there is a decreasing monotonic relationship between the extent of capital mobility and the significance of the coefficient on capital in a regression of output on endowments. We have no proof that capital mobility drives our result that capital is not a significant determinant of specialization. However, the empirical finding remains, and capital mobility seems to us to be the most plausible explanation.

In the next section, we will test the robustness of the result that capital is not significant. We have two categories of robustness check. If the true model is in fact non-linear, the imposition of linearity could be driving the result on the coefficient on capital. So first we test for non-linearities. Second, our data on output and factors are standard for the literature. But our measures of productivity differences are not. Since the difference between our results and previous work lies in the adjustment of factors by these productivity differences, we are concerned that our measure of technology differences drives our results. So we construct different measures of technology differences, and estimate again using these to adjust.

[37] An alternative to avoid this problem is to assume that there are productivity differences for other factors but not for capital. Then, conditional FPE will imply equalization of returns to effective units, which in the case of capital will be identical to natural units. We do not work with this assumption because, as we will see later, we observe differences in the returns to capital across countries. This can be explained either by differences in the productivity of capital across countries or by the failure of FPE, but it is inconsistent with the joint assumption of conditional FPE and identical productivity of capital in all countries.

4 Robustness

4.1 Tests for non-linearity

As we have just discussed, when FPE does not hold, the relationship between output and endowments is non-linear. Moreover, the relationship does not have to be the same across countries. But even if we do not believe in perfect FPE, on the assumption that the relationship can be approximated by the same non-linear function for all countries, we might want to estimate a model with output as a non-linear rather than a linear function of endowments. Given the size of our sample, the form of non-linearity we can estimate is limited. The best we can do is to include quadratic terms for each factor in each sector. We cannot include cross terms, as there are not enough degrees of freedom. The results of this estimation are reported in Table 11. First, the quadratic terms are not significant in general. Second, capital is significant at the 10% level in some sectors. But skilled and unskilled labor still play the major role.

We test this model against the restricted model where the coefficients on the quadratic terms are forced to equal zero in all sectors (the linear model). We cannot reject the joint linearity assumption. We test the hypotheses that each factor in turn can be excluded from this quadratic model. We cannot reject the restriction that capital can be excluded (both linear and quadratic terms). But we reject the restrictions that skilled labor and unskilled labor individually can be excluded.[38] We also test the hypotheses that there are quadratic terms in each factor individually against the linear model. We cannot reject linearity in each case. We want to point out that the power of these tests is low given that we have few observations and many parameters to estimate. To conclude, with the data we have, we cannot reject linearity as a good first approximation. But we are aware that this does not mean the true relationship is linear.

4.2 Technology I: Different TFP measures

The results we presented in Section 3 are based on adjusting factors using a measure of TFP calculated under the null hypothesis of FPE. If conditional FPE does not hold, our measure of TFP will be biased.[39] As an alternative, we can construct TFP measures based on the assumption of a Cobb-Douglas aggregate production function, as is frequently done. This assumption is inconsistent

[38] The F-statistic for this test on capital is 1.26. The F-statistic for skilled labor is 1.73. The F-statistic for unskilled labor is 2.79. The F-statistic for land is 0.82. The critical values are 1.39 and 1.59 at the 5% and 1% levels respectively.

[39] In particular for the case of only two factors, capital and labor, the FPE measure of TFP would be biased downwards from the true TFP for capital-abundant countries, and biased upwards for capital-scarce countries. This demonstration is due to Diego Comín.

with the null of conditional FPE. But since the difference between our results and previous work lies in the adjustment of factors by productivity differences, it is a sensible exercise to check how sensitive our results are to different reasonable measures of productivity differences. The Cobb-Douglas TFP measure is constructed as follows:

$$\begin{aligned} GDP^c &= a^c \prod_{f=1}^{F} \left(v_f^c\right)^{\alpha_f^c} \\ a^c &= \frac{GDP^c}{\prod_{f=1}^{F} \left(v_f^c\right)^{\alpha_f^c}} \end{aligned}$$

We use the shares of the factors in output to substitute in for the α_f^cs. If we assume the same production function in all countries, we need only the factor shares for a numeraire country to calculate the relative productivities. We choose an average of the OECD shares as numeraire. See Appendix B for details. The relative productivities we calculate are reported in Table 5. They are very similar to the productivities calculated under the null of FPE. The correlation between the two is 0.94.

The results from estimating using factors adjusted by the Cobb-Douglas TFP measure are reported in Table 12. They are very similar to our baseline results. Once again, the coefficient on capital is not often significantly different from zero, while the coefficients on skilled and unskilled labor are frequently significantly different from zero. Also, the sign of the estimated coefficients remains stable across the two specifications.

4.3 Technology II: Factor-specific productivities

Our estimates of productivity differences across countries have been derived so far under the assumption of Hicks-neutrality. We want to relax this assumption in order to check that the Hicks-neutral assumption is not driving our results. In this section, we allow productivity differences to be factor-specific, while maintaining the conditional FPE assumption. As we already explained, this is a more general assumption of technology differences, and it includes Hicks-neutrality as a particular case.[40] As we will see, factor-specific productivity differences have the nice property that they can accomodate some important features of the data which cannot be explained in a model with Hicks-neutral technology differences and conditional FPE.

[40] Trefler (1993) and Caselli and Coleman (2000) allow for factor-specific productivity differences. Trefler (1993) assumes conditional FPE as we do. Caselli and Coleman (2000) assume factor-specific differences in a CES aggregate production function. Harrigan and Zakrajšek (2000) implicitly allow for these differences by introducing country-specific fixed effects.

Conditional FPE with factor-specific productivities implies for each factor

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

We can then calculate factor productivities as

$$a_f^c = \frac{w_f^c}{w_f^{US}}$$

In order to do this, we need information on factor prices for each factor in each country. We calculate these from national accounts information, by dividing the total income to the factor in each country by the factor endowment. The details are given in Appendix B.[41] This methodology translates differences in factor returns directly into differences in productivities. Data quality problems in estimating factor returns have prevented us from taking this case as our baseline, but it is an obvious and worthwhile test of the robustness of our results.

Our estimates of factor-specific productivities are reported in Table 5. Note first that productivity differences across countries vary across factors. The most striking case is that of arable land.[42] But the productivity of each factor is positively correlated with the FPE-TFP measure. Second, the dispersion of returns to capital is smaller than the dispersion of returns to other factors. As we argued before, we expect capital mobility to attenuate the dispersion of returns to capital across countries. This translates in our specification into a lower dispersion of productivity differences for capital.[43] Thus, an advantage of factor-specific productivity differences is that they are able to capture this feature of the data. Third, conditional FPE together with the particular pattern of estimated productivities imply factor intensities in natural units more in accordance with the findings of Dollar et al. (1998), Dollar and Wolff (1993), and Davis and Weinstein (1998). With conditional FPE, unit input coefficients are equalized across countries in efficiency units. Since more productive countries are relatively more productive in the labor inputs than in capital, this means that they will use more capital relative to labor (in natural units) than less productive countries.

Given the factor specific productivities, we adjust the raw endowments, and use the adjusted endowments to estimate the equivalent of (20). The results are reported in Table 13. The pattern is very similar to the case of Hicks-neutral productivity differences. The coefficient on capital is

[41] In particular, following Blanchard (1997) and Gollin (1998) we adjust labor income to include imputed labor income to the self-employed.

[42] We do not find it unreasonable that this is the case.

[43] Differences in returns to capital across countries can be reconciled with perfect (financial) capital mobility if the law of one price for capital goods does not hold. In that case, perfect capital mobility imposes equalization of rates of return to capital, but not equalization of absolute returns.

significantly positive in only one sector (Non-ferrous metals, as before). The coefficients on skilled and unskilled labor are frequently significantly different from zero. Moreover, the pattern of positive and negative coefficients does not change much. Our finding that skilled and unskilled labor, not capital, are the most important factors driving specialization seems quite robust.

5 Conclusion

In the introduction, we point out a puzzling common result of most of the previous literature. Capital appears to be a crucial determinant of specialization, while other factors do not play an important role. In particular, an increase in the capital stock has a positive effect on the production of all manufacturing sectors. The uniformity of this result across sectors is a puzzle. It is also surprising in the light of recent work on the impact of trade that assumes capital is irrelevant for the pattern of specialization because of capital mobility. The contribution of this paper is to shed some light on this puzzle.

First, we show that capital is not in fact a crucial determinant of specialization in all manufacturing sectors. We show that if factor-augmenting technology differences (in our baseline case common across factors) are important, we should adjust factors by their relative efficiency in a regression of output on endowments. The failure to adjust for these differences drives the results of the previous literature. We calculate Hicks-neutral productivity differences, use these to adjust factors, and regress output on the adjusted factors. Our results reverse the conclusions of the previous literature. Skilled and unskilled labor are the important factors determining the structure of production, while the relative endowment of capital does not play a major role. We perform many checks to test the robustness of our findings. They turn out to be robust.

We go on to argue that our results are consistent with the view that capital is mobile, and therefore, not a determinant of specialization. We cannot prove that capital mobility is the driving force behind our results. But it appeals to us as the most plausible explanation. We think this result is interesting and important enough to deserve further scrutiny. In future work, we want to examine the role of capital mobility more carefully. On the theoretical side, we think the main challenge is to match the technology-adjusted factor proportions theory with a theory of capital mobility that can account for observed cross–country differences in factor returns. We discussed some of the problems in the paper, but we think it deserves further research. On the empirical side, we want first to repeat the exercise we have carried out here for years other than 1988. Capital mobility has increased in the last 30 years. If capital mobility is indeed driving the insignificance of the coefficient on capital in 1988, we expect the result to be stronger for the 1990s, and weaker for the 1970s. Second, we want to distinguish infrastructure from the rest of the capital stock.

Infrastructural investment is driven in large part by non-market forces. In consequence, the usual implications of capital mobility in terms of reducing the dispersion of returns to capital across countries should not apply so strongly for infrastructural capital. So we expect infrastructural capital to be a significant determinant of specialization. Third, our results are for the OECD. It is reasonable to think that capital mobility is weaker for developing countries. Introducing other countries into the analysis would be another informative exercise.

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A Appendix: Sources and construction

A.1 Output

Sectoral output data (gross output and value added) for 1988 comes from the UNIDO Industrial Demand-Supply Balance Database, 3-digit ISIC Codes.

GDP data comes from OECD National Accounts - Detailed Tables, 1983-1995 (OECD-DT). We want to take GDP at factor cost. We use as GDP the sum of Consumption of fixed capital, Compensation of employees paid by resident producers, and Operating surplus (Table 1). This is equivalent to subtracting Indirect taxes, Subsidies, and the Statistical discrepancy from the reported GDP measure. As explained in the text, in our baseline specification we consider residential contruction a consumption good. We therefore additionally subtract Gross rent (GR) from GDP (line 9, Table 2). This component represents on average 11% of GDP. Four countries do not report data on GR. Three of these report a more aggregated item, Gross Rent, Fuel, and Power (GRFP). We find the ratio of GR to GRFP for the countries where these data are available and use it to impute GR for the three countries reporting GRFP. 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 we use for calculating productivity differences and for weighing the observations. When we perform consistency checks using Total Capital, we use instead the unadjusted GDP.

All output measures are converted to US dollars using market exchange rates from IFS.

A.2 Endowments

The capital stock in 1988 comes from the PWT. 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. Unless specified, our measure of the capital stock does not include Residential Capital.

The labor force in 1988 also comes from the PWT. In order to construct the series on endowments of skilled and unskilled labor, we use data on educational attainment from the OECD publication *Education at a Glance* (1992 and 1993). The data reported is for various years. For most countries, the data refer to 1989, but for some they refer to 1987, 1988 or 1990. We define as skilled all those 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. Table C.1 in *Education at a Glance* gives the percentage of the total population aged 25-64 with each level of attainment. We are interested in the attainment of the labor force, not of the total population. Table C.5 gives labor force participation rates by educational attainment. Combining these two sets of information we obtain the percentage of the labor force in the skilled category. We apply this to total employment in order to get skilled and unskilled employment.

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

A.3 Exchange rates

Market exchange rates are yearly averages taken from International Financial Statistics.

A.4 Factor Prices

In order to construct our productivity indices, we need data on factor prices. The details of construction are given in Appendix B. Here, we will 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 International Labor Office *Yearbook of Labor Statistics* (ILO).

We estimate the ratio of skilled to unskilled wages from different sources. For the US, we estimate the ratio of skilled to unskilled wages from the Integrated Public Use Microdata Series (IPUMS) for 1990. This is a 1% sample of the 1990 US Population Census. From the European Community Household Survey, Wave I, Eurostat we also have this ratio for 11 other OECD countries in 1993: Austria, Belgium, Denmark, France, Greece, Ireland, Italy, Netherlands, Portugal, Spain and the UK (data for Austria is for 1994). For Australia, Canada, Norway, Finland, and Sweden, we obtain the ratio from the Luxembourg Income Project (years ranging from 1987 to 1992). For New Zealand we obtain the ratio from the International Social Survey Program 1992. We do not have data for Germany, Japan, and Turkey. We assume for Germany the ratio in Austria, for Turkey the ratio in Greece, and for Japan, we assume a ratio of 1.5.

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 comes from OECD-DT

B Appendix: Productivity estimates

B.1 FPE-consistent measure

This measure is:

$$a^c = \frac{GDP^c}{\left(\sum_{f=1}^{F} v_f^c w_f^{US}\right)}$$

so we require data on factor prices for the numeraire country, the US.

From OECD-DT, we can 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 from the 1990 IPUMS. Note that the definition we use of skilled and unskilled is equivalent to the definition we use in calculating endowments. 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:

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

B.2 Factor-specific measures

The measure for factor f in country c is:

$$a_f^c = \frac{w_f^c}{w_f^{US}}$$

To calculate these a_f^c, we need estimates of factor prices for each country. We follow here the same methodology used to calculate factor prices for the US. First, we divide total income into the total compensation of each factor, and then we divide the latter by the quantity of each factor to obtain rental prices. Unavailability of data forces us to impute some figures.

We first divide AGDP into compensation of employees (income to skilled and unskilled labor), and residual income (income to capital and land), using data from OECD-DT. Income of self-employed workers is not included into compensation of employees. Following Gollin (1998) and Blanchard (1997), we impute to the self-employed the average wage rate and we add this income to the compensation of employees. This gives an adjusted measure of total compensation of labor. The average wage rate we use to do this is the ratio of compensation of employees over the employed population. On average, the self-employed represent 20% of the employed population. The percentage tends to be much higher for less developed countries (in Greece the share is 48% and in Turkey it is 61%). In the US, the share of self-employed workers is only 8.6% (This is why we do not perform this adjustment to calculate factor prices in the US as described in the previous section).

We divide total adjusted income to labor into income to skilled and income to unskilled labor as described for the US, using the ratio of skilled to unskilled wages for each country. We divide the residual income into income to capital and income to land by estimating income to land and getting the compensation of capital as a residual. The procedure to estimate income to land is first to estimate for each country the operating surplus in the sector Agriculture and Hunting (AH), and then to impute income to land from this total according to the ratio of these two variables for the US (the only country for which we have income to land). Ten countries report data on Operating Surplus in AH (Table 13, line 2). They are: Canada, Denmark, Finland, France, Germany, Netherlands, New Zealand, Norway, Portugal, and Sweden. For these countries, we take the average ratio of operating surplus to value added in AH. We apply this average to estimates of value added in AH to estimate the operating surplus in AH for the rest of the countries. For four countries we have direct data on value added in AH. They are Greece, Italy, Turkey, and the US (for the US data comes from Survey of Current Business). For the remaining seven countries we estimate value added in AH. In order to do this, we calculate two ratios for the original 10 countries for which we have complete data. The first is the ratio of value added in AH to value added in Agriculture, Hunting, Fishing, and Forestry (AHFF). The second is the ratio of arable land to the sum of arable land, forestry, and woodland (from FAO). We run a linear OLS regression on these two variables. We use the estimated coefficients to predict the share of value added in AH in each country. We apply these predicted values to value added in AHFF to obtain value added in AH.

Once we have divided total income into our four factors, we proceed as already explained to calculate factor prices.

B.3 Cobb-Douglas measure

The measure is:

$$a^c = \frac{GDP^c}{\prod_{f=1}^{F} \left(v_f^c\right)^{\alpha_f^c}}$$

so we require data on factor shares. Factor shares differ substantially across the countries in our sample. So we use an average share to estimate TFP.

Average shares are obtained from the calculations in the previous section. The average capital share is 20.8%.[44] The average skilled labor share is 49.4%. The average unskilled labor share is 27.5%. The average land share is 2.3%.

[44]This share is small relative to usual measures for two reasons. First, we have subtracted Gross Rent from GDP. This is income fully attributable to capital. Second, we have recategorized part of the mixed income of the self-employed into compensation of labor.

Table 1. Rybczynski equations with unadjusted factors (all countries)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Land	Constant	APE	Obs.
Food products	3142.9	1959.3	-613.0 **	-98.4	5.14 ***	0.23	20
Beverages	820.3	229.9	-69.8	-21.5	0.34 *	0.26	21
Tobacco	361.2	184.0	47.2 *	-35.1 *	-0.06	0.54	21
Textiles	2970.8 ***	-548.6	323.7 ***	-98.7	0.14	0.58	21
Wearing apparel	1239.2 ***	-157.3	48.2	-12.6	0.04	0.66	21
Leather products	499.9 **	-158.7 *	9.0	-5.7	0.05	0.99	20
Footwear	830.2 ***	-277.8 **	30.8	-17.7	-0.01	1.56	20
Wood products	1806.0 **	-163.9	-133.5 *	13.8	0.24	0.60	21
Furniture, exc. Metal	1151.9 **	17.7	-58.9	-30.7	-0.11	0.49	21
Paper and products	3971.4 *	-365.4	-170.5	-58.0	0.10	0.65	21
Printing and publishing	1867.8 **	517.1	-215.7 ***	-40.2	0.05	0.39	21
Industrial chemicals	3472.1 *	415.2	113.5	-224.1 *	-0.35	0.47	21
Other chemicals	1095.4	714.6	-49.6	-83.6	0.35	0.37	21
Rubber products	362.5	137.0	4.5	-16.5	-0.07	0.49	21
Plastic products	981.0	350.2	-79.5	-34.8	-0.06	0.41	20
Pottery, china, earth.	353.1 **	-79.6	39.4 ***	-18.1 **	-0.05	0.72	19
Glass and products	267.6	74.7	12.7	-16.7	0.03	0.48	20
Other non-met.min.pr.	1199.3 **	200.3	-15.4	-38.5	0.22	0.28	20
Iron and steel	3172.5 ***	170.3	105.0	-98.9 *	-1.06 ***	0.44	20
Non-ferrous metals	2491.0 ***	-284.9	-127.0 **	30.5	-0.37	0.72	20
Fabricated metal prod.	2650.7 ***	642.4	-227.1 ***	-65.5	-0.13	0.25	20
Machinery, exc. elect.	1825.8	2574.6 **	-282.8	-333.6 **	0.33	0.80	20
Machinery electric	1757.7	2274.5 *	-102.6	-346.3 **	-0.34	0.55	20
Transport equipment	6988.5 **	816.5	-311.0	-151.0	-2.52 **	0.79	20
Prof. & scient. equip.	-445.2	595.1 **	-72.5	-25.5	0.19	1.68	20
					Overall:	0.61	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 2. Coefficients determining SCA (unadjusted factors, all countries)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Land
Food products	1096	-37	-1834	-110
Beverages	467	-115	-281	-24
Tobacco	181	8	-60	-36
Textiles	2234	-1267	-116	-103
Wearing apparel	920	-469	-143	-14
Leather products	431	-226	-32	-6
Footwear	764	-343	-9	-18
Wood products	1487	-476	-324	12
Furniture, exc. Metal	944	-185	-183	-32
Paper and products	3351	-970	-540	-62
Printing and publishing	1173	-160	-630	-44
Industrial chemicals	2530	-504	-449	-230
Other chemicals	347	-15	-496	-88
Rubber products	161	-60	-116	-18
Plastic products	497	-122	-368	-38
Pottery, china, earth.	307	-125	12	-18
Glass and products	145	-45	-60	-17
Other non-met.min.pr.	779	-209	-266	-41
Iron and steel	2360	-622	-380	-104
Non-ferrous metals	2093	-673	-365	28
Fabricated metal prod.	1714	-271	-786	-71
Machinery, exc. elect.	77	869	-1326	-344
Machinery electric	77	636	-1105	-356
Transport equipment	4862	-1257	-1580	-163
Prof. & scient. equip.	-791	258	-279	-28

Note: Reported coefficients correspond to equation (11): $B_{jf} = r_{jf} - (Y_j^w/Y^w)w_f$

Table 3. Factor abundance: The "endowments paradox"

Country	Capital		Skilled		Unskilled		Land	
	Coeff.	Rank	Coeff.	Rank	Coeff.	Rank	Coeff.	Rank
AUS	1.288	4	1.028	9	1.249	10	6.752	2
AUT	1.108	8	1.093	6	0.880	15	0.426	14
BEL	1.068	14	0.646	18	1.564	7	0.179	19
CAN	1.238	5	1.104	5	0.672	19	3.496	3
DEN	1.081	12	0.935	11	1.199	12	0.945	10
FIN	1.221	6	0.815	15	1.010	14	0.864	11
FRA	1.082	11	0.814	16	1.321	9	0.699	12
GER	1.071	13	1.038	8	0.437	20	0.364	16
GRE	1.512	2	1.118	4	3.857	3	1.526	7
IRE	0.949	17	0.871	12	2.364	5	0.976	9
ITA	0.918	20	0.458	21	1.937	6	0.368	15
JAP	0.986	15	1.016	10	0.708	18	0.051	21
NET	0.940	18	0.865	13	1.036	13	0.134	20
NOR	1.206	7	0.811	17	0.723	17	0.331	17
NZE	1.394	3	1.154	3	1.553	8	2.268	4
POR	1.095	10	0.467	20	9.258	2	1.728	5
SPA	1.097	9	0.548	19	3.144	4	1.567	6
SWE	0.962	16	0.820	14	0.782	16	0.546	13
TUR	2.193	1	2.599	1	22.061	1	9.577	1
UK	0.810	21	1.311	2	1.201	11	0.320	18
USA	0.932	19	1.089	7	0.377	21	1.353	8
Total	1.000		1.000		1.000		1.000	

Note: Factor abundance is calculated as $(v^c_f/GDP^c)/(v^w_f/GDP^w)$.

Table 4. Rybczynski equations with unadjusted factors (Turkey excluded)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Arable	Constant	APE	Obs.
Food products	2356.6	2285.8	-478.7	-81.6	5.05 ***	0.24	19
Beverages	151.9	511.2 *	52.2	-7.7	0.24	0.25	20
Tobacco	461.1	142.0	29.0	-37.2 *	-0.04	0.58	20
Textiles	618.3	441.3	753.4 ***	-49.9	-0.19	0.40	20
Wearing apparel	419.8	187.5	197.9 ***	4.4	-0.07	0.57	20
Leather products	213.1	-39.6	58.0 **	0.5	0.02	0.76	19
Footwear	212.8	-21.5	136.3 ***	-4.5	-0.08	0.93	19
Wood products	1634.5	-91.7	-102.2	17.3	0.22	0.62	20
Furniture, exc. Metal	1126.1	28.6	-54.2	-30.2	-0.11	0.51	20
Paper and products	4517.7	-595.3	-270.2	-69.3	0.18	0.69	20
Printing and publishing	1235.1	783.3	-100.2	-27.1	-0.04	0.37	20
Industrial chemicals	2087.9	997.7	366.3	-195.4	-0.55	0.43	20
Other chemicals	-758.1	1494.5 ***	288.9 *	-45.1	0.09	0.24	20
Rubber products	108.8	243.7 *	50.8	-11.2	-0.11	0.46	20
Plastic products	-69.8	786.6 **	99.9	-12.4	-0.19	0.31	19
Pottery, china, earth.	107.7	21.8	80.8 ***	-12.9 *	-0.08 *	0.60	18
Glass and products	16.0	179.1	55.7 *	-11.3	-0.01	0.43	19
Other non-met.min.pr.	236.7	600.0 *	149.0 *	-17.9	0.10	0.24	19
Iron and steel	3448.8 ***	53.8	54.5	-104.6 *	-1.02 ***	0.47	19
Non-ferrous metals	2967.5 ***	-485.8	-214.1	20.7	-0.31	0.82	19
Fabricated metal prod.	1565.3	1093.1 **	-41.7	-42.2	-0.26	0.22	19
Machinery, exc. elect.	2153.6	2438.5	-338.7	-340.6 *	0.37	0.84	19
Machinery electric	-747.1	3314.4 **	325.2	-292.7 *	-0.66	0.49	19
Transport equipment	2535.7	2665.3	449.5	-55.8	-3.09 ***	0.73	19
Prof. & scient. equip.	-886.9	778.5 **	3.0	-16.1	0.14	1.54	19
					Overall:	0.55	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 5. Measures of Productivity Differences

country	HN-FPE		HN-CD		Factor-specific productivities							
					Capital		Skilled		Unskilled		Land	
	A^{FPE}	Rank	A^{CD}	Rank	Ak	Rank	As	Rank	Au	Rank	At	Rank
AUS	0.80	17	0.69	17	0.90	13	0.75	15	0.94	14	0.53	21
AUT	0.88	12	0.81	11	0.93	10	0.83	12	0.98	13	5.90	8
BEL	1.03	4	0.92	8	0.96	8	0.93	9	1.25	2	9.64	4
CAN	0.86	13	0.78	15	0.92	12	0.83	13	1.10	10	0.57	20
DEN	0.92	11	0.80	13	0.62	20	0.92	10	1.16	5	4.05	13
FIN	0.98	8	0.84	9	0.75	16	1.06	2	1.10	9	4.07	12
FRA	0.97	10	0.84	10	0.85	15	0.96	6	1.06	11	4.79	10
GER	0.99	7	0.97	4	1.04	5	0.96	7	1.13	6	4.53	11
GRE	0.56	19	0.51	20	0.63	19	0.44	19	0.56	19	7.71	7
IRE	0.82	15	0.75	16	0.86	14	0.67	17	0.87	16	9.37	6
ITA	1.14	1	1.05	1	1.36	1	0.93	8	1.18	4	9.68	3
JAP	0.98	9	0.95	5	0.74	17	1.01	4	1.11	8	34.81	1
NET	1.03	5	0.94	6	1.26	2	0.89	11	1.13	7	28.21	2
NOR	1.04	3	0.93	7	0.93	11	1.05	3	1.34	1	9.37	5
NZE	0.72	18	0.62	19	0.68	18	0.66	18	0.87	15	3.41	14
POR	0.45	20	0.68	18	1.04	6	0.44	20	0.35	20	1.75	16
SPA	0.83	14	0.80	12	0.94	9	0.77	14	0.80	18	2.93	15
SWE	1.10	2	0.97	3	1.10	3	1.08	1	1.24	3	1.74	18
TUR	0.16	21	0.21	21	0.58	21	0.13	21	0.10	21	1.75	17
UK	0.81	16	0.79	14	1.07	4	0.71	16	0.81	17	5.42	9
USA	1.00	6	1.00	2	1.00	7	1.00	5	1.00	12	1.00	19
Coefficient of variation	0.27		0.24		0.22		0.30		0.32		1.21	

Matrix of Correlations

	A^{FPE}	A^{CD}	Ak	As	Au	At
A^{FPE}	1.00	0.94	0.53	0.96	0.96	0.29
A^{CD}		1.00	0.66	0.91	0.85	0.32
Ak			1.00	0.38	0.38	0.14
As				1.00	0.95	0.24
Au					1.00	0.27
At						1.00

Table 6. Correlations between measures of factor abundance and A^{FPE}

	Capital	Skilled	Unskilled	Land
Corr (A^{FPE}, adjusted factor)	0.833	0.559	-0.714	-0.252

Note: A^{FPE} is the productivity measure consistent with Hicks-neutrality and FPE.

Table 7. Rybczynski equations with A^{FPE} adjusted factors (all countries)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Land	Constant	APE	Obs.
Food products	1695.2	2728.2	-83.3	-29.3	4.95 ***	0.24	20
Beverages	-129.9	589.2 *	190.6	5.2	0.28 *	0.28	21
Tobacco	-414.9	450.5 *	272.7 ***	-24.1	-0.03	0.60	21
Textiles	-1696.4	1053.4 *	1691.2 ***	-12.1	0.00	0.40	21
Wearing apparel	-305.1	372.3 *	499.6 ***	26.2	0.00	0.54	21
Leather products	240.9	-78.1	99.9 **	0.8	0.04	0.87	20
Footwear	306.7	-101.2	185.5 ***	-6.0	-0.03	1.31	20
Wood products	1549.7	-31.9	-181.9	46.1	0.39	0.58	21
Furniture, exc. Metal	990.2	71.5	8.8	-20.4	-0.06	0.49	21
Paper and products	3982.3	-337.9	-319.0	-17.1	0.49	0.67	21
Printing and publishing	979.0	938.1 **	-79.5	0.5	0.13	0.34	21
Industrial chemicals	55.4	1733.3 *	1129.9 **	-175.0	-0.39	0.38	21
Other chemicals	-1620.6	1816.7 ***	595.2 ***	-27.5	0.21	0.24	21
Rubber products	-335.9	396.3 ***	194.9 ***	-1.3	-0.09	0.42	21
Plastic products	-364.7	899.0 ***	219.3 *	-1.3	-0.10	0.32	20
Pottery, china, earth.	-30.0	49.3	175.4 ***	-12.9 *	-0.07 **	0.46	19
Glass and products	-234.1	264.8 ***	155.8 ***	-7.3	0.00	0.34	20
Other non-met.min.pr.	-453.3	810.9 ***	415.4 ***	2.0	0.18	0.24	20
Iron and steel	375.3	1130.7 *	1046.2 ***	-43.3	-0.99 ***	0.46	20
Non-ferrous metals	2169.1 **	-213.1	-34.7	66.7	-0.18	0.98	20
Fabricated metal prod.	647.9	1492.5 ***	131.1	-3.4	-0.02	0.21	20
Machinery, exc. elect.	922.5	3175.2 **	22.2	-333.9 **	0.40	0.64	20
Machinery electric	-2348.5	4096.7 ***	762.0	-304.1 **	-0.39	0.42	20
Transport equipment	47.6	3568.5 **	1163.7 *	50.4	-2.46 ***	0.59	20
Prof. & scient. equip.	-890.3	849.6 **	-31.9	-16.3	0.14	1.43	20
					Overall:	0.54	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 8. Coefficients determining SCA (A^{FPE} adjusted factors, all countries)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Land
Food products	-351	732	-1304	-41
Beverages	-483	245	-20	3
Tobacco	-595	275	165	-25
Textiles	-2433	335	1252	-16
Wearing apparel	-625	61	309	24
Leather products	172	-146	59	0
Footwear	240	-166	146	-6
Wood products	1230	-343	-373	44
Furniture, exc. Metal	782	-132	-115	-22
Paper and products	3362	-943	-689	-21
Printing and publishing	284	260	-494	-4
Industrial chemicals	-887	814	568	-180
Other chemicals	-2369	1087	149	-32
Rubber products	-537	200	75	-2
Plastic products	-849	427	-70	-4
Pottery, china, earth.	-76	4	148	-13
Glass and products	-356	146	83	-8
Other non-met.min.pr.	-873	401	165	0
Iron and steel	-437	338	561	-48
Non-ferrous metals	1771	-601	-272	64
Fabricated metal prod.	-288	579	-428	-9
Machinery, exc. elect.	-826	1470	-1021	-344
Machinery electric	-4029	2458	-241	-314
Transport equipment	-2079	1495	-105	38
Prof. & scient. equip.	-1236	513	-238	-18

Note: Reported coefficients correspond to equation (11): $B_{jf} = r_{jf} - (Y_j^w/Y^w)w_f$

Table 9. Effects of educational upgrading on specialization

	r(skilled)-r(unskilled)	Std.Dev.	t-stat.	
Food products	2812	1873	1.50	
Beverages	399	279	1.43	
Tobacco	178	216	0.82	
Textiles	-638	509	-1.25	
Wearing apparel	-127	207	-0.62	
Leather products	-178	96	-1.85	*
Footwear	-287	133	-2.16	**
Wood products	150	489	0.31	
Furniture, exc. Metal	63	286	0.22	
Paper and products	-19	1249	-0.02	
Printing and publishing	1018	421	2.42	**
Industrial chemicals	603	963	0.63	
Other chemicals	1221	439	2.78	**
Rubber products	201	113	1.78	*
Plastic products	680	275	2.48	**
Pottery, china, earth.	-126	57	-2.23	**
Glass and products	109	88	1.23	
Other non-met.min.pr.	396	272	1.45	
Iron and steel	85	600	0.14	
Non-ferrous metals	-178	444	-0.40	
Fabricated metal prod.	1361	437	3.11	***
Machinery, exc. elect.	3153	1343	2.35	**
Machinery electric	3335	1229	2.71	**
Transport equipment	2405	1509	1.59	
Prof. & scient. equip.	881	327	2.70	**

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 10. Elasticity of output with respect to factor endowments

	Capital	Skilled	Unskilled	Land
Food products	0.16	0.50	-0.01	-0.01
Beverages	-0.09	0.79	0.22	0.01
Tobacco	-0.83	1.67	0.76	-0.20
Textiles	-0.93	1.06	1.05	-0.02
Wearing apparel	-0.39	0.88	0.75	0.08
Leather products	1.46	-0.91	0.71	0.02
Footwear	1.98	-1.24	1.40	-0.11
Wood products	1.23	-0.05	-0.28	0.12
Furniture, exc. Metal	1.29	0.18	0.03	-0.11
Paper and products	1.70	-0.27	-0.26	-0.03
Printing and publishing	0.42	0.74	-0.08	0.00
Industrial chemicals	0.02	0.97	0.54	-0.22
Other chemicals	-0.68	1.35	0.38	-0.04
Rubber products	-0.71	1.51	0.59	-0.01
Plastic products	-0.25	1.12	0.26	0.00
Pottery, china, earth.	-0.25	0.80	1.56	-0.62
Glass and products	-0.57	1.19	0.54	-0.07
Other non-met.min.pr.	-0.25	0.85	0.33	0.00
Iron and steel	0.17	0.96	0.80	-0.07
Non-ferrous metals	2.31	-0.43	-0.08	0.24
Fabricated metal prod.	0.18	0.76	0.07	0.00
Machinery, exc. elect.	0.22	1.35	0.01	-0.38
Machinery electric	-0.57	1.81	0.33	-0.35
Transport equipment	0.01	1.46	0.50	0.04
Prof. & scient. equip.	-2.66	4.38	-0.25	-0.21

Note: reported elasticities are calculated as: $e_{jf} = r_{jf} * \text{mean}(v_f/Y_j)$

Table 11. Rybczynski equations with A^{FPE} adjusted factors and non-linear terms (all countries)

Dependent Variable: gross output — Capital Measure: Non-residential capital
Weight: GDP-adj — Output conversion: Exch. Rates
Constant: Included

	Capital	Skilled	Unsk.	Land	Cap.^{2}	Skill.^{2}	Unsk.^{2}	Land^2	Cons.	APE	Obs.
Food products	-2856	5007	-961	-243	107807	-45063	174731	6712	6.04 ***	0.23	20
Beverages	-242	659	36	37	-56104	7998	26342	-643	0.36	0.28	21
Tobacco	-677	634	438 **	-72	76557	-14773	-25460	1013	-0.13	0.60	21
Textiles	-1954	947	1996 ***	-16	260545	-33023	-65429	13	-0.05	0.33	21
Wearing apparel	-508	362	441 **	45	49933	-5102	4992	-302	0.11	0.49	21
Leather products	182	-100	-17	35	-27224	5771	17254 *	-657	0.12 *	0.63	20
Footwear	187	-43	162	-24	4061	-1720	5615	482	0.02	1.25	20
Wood products	3367 *	-889	-182	252	-245878	49491	-11698	-5246	0.02	0.50	21
Furniture, exc. Metal	1185	105	42	-41	-68141	7121	633	367	-0.16	0.47	21
Paper and products	8789 *	-2517	-120	380	-606798	118240	-52118	-10496	-0.52	0.61	21
Printing and publishing	2913 *	5	-335	182	-355915 *	65188	37667	-4412	0.00	0.31	21
Industrial chemicals	-710	2592	2095 ***	-603	279653	-67074	-128216	9346	-0.92	0.37	21
Other chemicals	-3286 *	2474 ***	689 **	-112	319258	-52515	-20259	2257	0.44	0.21	21
Rubber products	-604	448 **	135 *	41	44147	-4496	4033	-908	-0.03	0.30	21
Plastic products	-1273	1050 **	4	105	123097	-11878	19359	-2014	0.18	0.21	20
Pottery, china, earth.	-356 *	200 *	161 ***	-33	37782	-7337	3495	551	-0.01	0.46	19
Glass and products	-628 *	409 **	142 **	-12	59186	-9325	410	208	0.07	0.29	20
Other non-met.min.pr.	-546	846	346	79	-20856	5164	6098	-1777	0.14	0.20	20
Iron and steel	541	981	1157 **	184	51126	2203	-42099	-5639	-1.33 **	0.42	20
Non-ferrous metals	3292 *	-573 **	196	92	-128345	20766	-35576	-1111	-0.58	0.83	20
Fabricated metal prod.	273	1375 *	23	265 *	106669	-1675	-13580	-6143 *	-0.05	0.17	20
Machinery, exc. elect.	-3911	4816 *	-523	-308	604890	-91924	64540	1167	1.51	0.56	20
Machinery electric	-7741 *	5637 ***	699	-87	1036476 **	-141286 *	-56469	-3644	0.39	0.37	20
Transport equipment	-940	3029	1119	524	496770	-37268	-68831	-10564	-2.26 *	0.49	20
Prof. & scient. equip.	-1276	832 *	-83	-117	111891	-16295	10151	2725	0.47 **	1.19	20
									Overall:	0.47	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 12. Rybczynski equations with A^{CD} adjusted factors (all countries)

Dependent Variable: gross output — Capital Measure: Non-residential capital
Weight: GDP-adj — Output conversion: Exch. Rates
Constant: Included

	Capital	Skilled	Unskilled	Land	Constant	APE	Obs.
Food products	2613.2	2624.5	-487.8	-0.4	5.38 ***	0.25	20
Beverages	97.9	566.7	76.2	9.7	0.37 **	0.29	21
Tobacco	-364.1	492.1 *	197.0 **	-24.6	0.02	0.59	21
Textiles	-1247.7	1096.0 *	1402.4 ***	-8.3	0.09	0.40	21
Wearing apparel	-101.3	368.9	388.9 ***	34.9	0.04	0.56	21
Leather products	329.3	-99.6	76.5 **	1.2	0.05	0.87	20
Footwear	453.0	-137.8	162.5 ***	-7.2	-0.03	1.32	20
Wood products	1841.5	-120.9	-146.0	60.9	0.35	0.60	21
Furniture, exc. Metal	1209.4 *	29.3	-32.1	-19.9	-0.02	0.46	21
Paper and products	4521.3	-476.2	-252.6	-0.4	0.43	0.65	21
Printing and publishing	1353.2	887.1 *	-129.7	9.4	0.19	0.33	21
Industrial chemicals	732.1	1743.9	894.6 **	-191.5	-0.26	0.36	21
Other chemicals	-1315.4	1856.7 ***	432.6 **	-26.9	0.32	0.24	21
Rubber products	-257.7	411.1 ***	141.8 ***	0.7	-0.06	0.44	21
Plastic products	-150.6	906.6 ***	136.8	0.8	-0.04	0.33	20
Pottery, china, earth.	23.7	48.7	147.9 ***	-14.3 *	-0.06 *	0.49	19
Glass and products	-182.3	276.8 **	122.2 ***	-7.3	0.02	0.36	20
Other non-met.min.pr.	-222.5	813.9 **	287.9 **	7.2	0.26	0.27	20
Iron and steel	923.2	1146.1	735.9 **	-33.8	-0.80 **	0.45	20
Non-ferrous metals	2592.4 **	-313.9	-121.4	86.8	-0.13	0.98	20
Fabricated metal prod.	1121.1	1476.7 ***	19.8	4.5	0.09	0.20	20
Machinery, exc. elect.	1522.0	3303.6 **	-162.7	-374.8 **	0.63	0.65	20
Machinery electric	-1869.5	4287.0 ***	573.0	-352.8 **	-0.21	0.41	20
Transport equipment	1299.2	3521.7 **	802.2	92.7	-2.27 ***	0.55	20
Prof. & scient. equip.	-957.5	922.6 **	-39.8	-17.2	0.16	1.48	20
						0.54	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 13. Rybczynski equations with factor-specific productivity adjusted factors (all countries)

Dependent Variable: gross output
Weight: GDP-adj
Constant: Included

Capital Measure: Non-residential capital
Output conversion: Exch. Rates

	Capital	Skilled	Unskilled	Land	Constant	APE	Obs.
Food products	-4951.7	4952.3 ***	2353.1	-12.3	4.50 ***	0.22	20
Beverages	-854.6	755.7 ***	560.3 **	7.6	0.15	0.30	21
Tobacco	663.6	-34.5	-102.8	23.8 **	-0.09	0.57	21
Textiles	718.7	-217.7	1310.4 **	41.2	-0.15	0.55	21
Wearing apparel	325.2	82.5	411.5 *	11.5	-0.04	0.64	21
Leather products	85.1	-25.7	183.0 **	-6.3	0.06	0.77	20
Footwear	228.5	-87.2	295.2 ***	-15.2 ***	0.04	1.23	20
Wood products	1649.2	252.0	-384.0	-39.3 *	0.74 **	0.51	21
Furniture, exc. Metal	93.4	425.0	283.3	-21.2	0.02	0.45	21
Paper and products	2642.1	705.9	-537.0	-71.7	1.11	0.51	21
Printing and publishing	-355.5	1521.2 ***	345.7	-23.6	0.23	0.26	21
Industrial chemicals	3112.6	266.0	541.2	-37.3	-0.01	0.41	21
Other chemicals	-1084.0	1332.0 **	885.9 *	9.0	0.11	0.31	21
Rubber products	80.1	193.2	119.4	8.1	-0.11	0.50	21
Plastic products	-504.0	860.1 ***	467.9 *	-0.2	-0.14	0.30	20
Pottery, china, earth.	177.8	-71.1	152.2 **	-1.5	-0.05	0.84	19
Glass and products	69.8	108.0	125.9	1.5	0.01	0.44	20
Other non-met.min.pr.	-767.7	801.8 ***	688.0 **	12.1	0.06	0.23	20
Iron and steel	2141.7	374.7	279.7	46.2 *	-1.05 **	0.37	20
Non-ferrous metals	2971.6 **	-150.1	-674.0	-1.7	-0.01	0.72	20
Fabricated metal prod.	38.1	1758.3 ***	392.5	-15.3	0.08	0.17	20
Machinery, exc. elect.	-2502.6	4010.3 ***	967.8	-18.2	0.39	0.68	20
Machinery electric	-2811.1	3522.4 **	1493.1	-0.5	-0.50	0.52	20
Transport equipment	1270.0	3113.9 **	1388.0	-38.0	-2.14 **	0.56	20
Prof. & scient. equip.	-1277.2	886.2 ***	278.9	2.5	0.06	1.27	20
					Overall:	0.53	

Notes:
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level