Essays on
Trade, Growth and Applied Econometrics

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AKADEMISK AVHANDLING

**Som för avläggande av ekonomie doktorsexamen vid Handelshögskolan i Stockholm framläggs för offentlig granskning
2001-05-30, kl 15.15
I sal 750 Handelshögskolan
Sveavägen 65**

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Dissertation for the Degree of Doctor of Philosophy,
Ph.D in Economics. Stockholm School of Economics 2001

ISBN nr 91-7258-567-6

Keywords:
Trade, Technology, Growth, Convergence, Forecasting

Printed by:
Elanders Gotab, Stockholm 2001

Distributed by:
EFI, The Economic Research Institute
Stockholm School of Economics
P O Box 6501, SE 1-113 83 Stockholm, Sweden
www.hhs.se/efi

To
Kristina
Samuel and Gabriel

Acknowledgements

Ten years ago, a PhD in Economics seemed to me as something far too time-consuming for an impatient student like myself; and certainly nothing that I would spend years of work on. The opportunity to write my MSc thesis under the supervision of Lars Lundberg and Pär Hansson convinced me, however, that although time consuming to write a PhD thesis, it can also an adventure.

Along the way, Lars Lundberg has been inspiring, supportive and encouraging. Lars has always underlined the importance of keeping in mind the real objectives of economic analysis, that is to say, beyond the algebraic and econometric exercises. Thank you, Lars! I am indebted to both Lars and Pär for their invaluable help in the course of my work. They have patiently devoted their time to discuss minor and major theoretical and econometric problems and I thank them for that.

It goes without saying that Ari Kokko, my advisor at the Stockholm School of Economics, deserves my gratitude. Ari is a person who never runs out of ideas and has given me unending support along the way. Thank you Ari!

Working at FIEF has involved interaction with researchers interested in other fields than International Economics. Among these, I would especially like to thank Per Lundborg and Mahmood Arai. When doing econometrics there has been an element of security in having Mårten Palme at the Stockholm School of Economics within an arm's length distance in order to discuss various econometric issues. Thank you all!

I am happy to have shared Joakim Persson's experience in a joint paper on convergence. I am also glad to have co-authored a paper predicting tourism flows with Jonas Nordström who finished his PhD a year ago.

I am grateful to the staff at FIEF and seminar participants at the Stockholm School of Economics for invaluable comments. I would especially like to thank the director at FIEF, Sten Johansson, for generously providing me with office space and full access to FIEF equipment.

I would also like to express my sincere gratitude to *Jakob Wallenbergs Forskningsstiftelse* and *HSFR* (*the Swedish Council for Research in Humanities and Social Science*) for generous financial support.

Lastly, I would like to thank my life companion, Kristina, for her unfailing support and understanding. Over these years, Samuel and Gabriel have been added to our family. Having this family has helped me to stay focused and kept me from getting bogged down on hairsplitting issues. One must appreciate the truly important things in life.

Stockholm April 2001

Patrik Gustavsson

Contents

Introduction and Summary

This dissertation consists of five essays. Three of these study countries' specialisation patterns combining the two classical paradigms of trade theory, namely the Ricardian (technology) and the Heckscher–Ohlin (factor endowments) framework. Of the remaining two essays, one studies convergence in per capita income among the Swedish counties and the other is methodological in that we investigate the issue of how seasonal unit roots and joint modelling may affect forecasts. In each of these essays, an empirical investigation is applied.

To undertake careful empirical investigations and match them against explicit theoretical models is an inspiring challenge where we may find pleasure as well as challenging puzzles. This give and take relationship may stimulate both sides in that theory can strongly influence how to approach a problem empirically and vice versa. Stylised facts and empirical regularities can boost theoretical model building.

Each essay is self-contained. However, I recommend reading the first three in the order they are presented. The fourth and fifth essays, on the other hand, are independent from the other essays.

The first essay looks at how technology, measured by total factor productivity (TFP) and endowments, jointly determines countries' specialisation patterns.

The main findings are that endowments and technology jointly determine trade patterns. In the level-analysis we find indications of scale effects at the firm level and that TFP turns out to be a poor determinant in explaining specialisation whereas endowments, and in particular natural resources are significant.

When analysing changes in specialisation and trade patterns, TFP growth is found to be a significant explanatory variable. These contradictory results, i.e., that TFP is not significant when studying levels but is when studying changes, may to some extent be explained by potential time invariant measurement errors that are differenced out when analysing changes. There is also evidence for an increased specialisation of human capital intensive production in countries with a high growth rate in the national supply of skilled labour.

Essay two takes the analysis one step further by going behind the black box of technology and relating this to its sources, where R&D is taken to be the new main object of the study. The analysis reveals that competitiveness is determined not only by R&D performance of the firm, but also that industry- and economy-wide stocks of knowledge are important, indicating the presence of local externalities in R&D. Further results point to scale effects in R&D at the firm level and that the impact of R&D is higher in high- and medium- than in low-tech industries.

The third essay focus on changes in countries' specialisation patterns. In the model building stage, we make the R&D process endogenous. Through domestic input-output linkages, we build in trade-transmitted technology transfers. Econometrically, we find indications of R&D at the firm level to be the main engine shaping technology and competitiveness. There is also evidence of scale effects in R&D at the firm level.

Analysing capital accumulation, we find that countries with relatively high capital accumulation increase their specialisation in capital-intensive industries. We also find that capital abundant countries have the highest rate of capital accumulation. Together, this indicates an increased concentration of capital-intensive industries in capital abundant countries.

Analysing human capital accumulation in an analogous manner, we find that countries with relatively high human capital accumulation increase their specialisation in human capital intensive industries. However, we find that countries with a relatively high human capital accumulation are those with initially small human capital stocks, indicating convergence in human capital abundance among the countries in the sample. How industries interact, and industrial interdependence, are analysed, and we find significant econometric evidence of interdependence between domestic industries with strong input-output linkages.

In the fourth essay, we analyse convergence in per capita income among the Swedish counties during the period 1911-93. Some innovative features in this essay are that we explicitly introduce distance in the econometric analysis and construct regional price indices. In the econometric analysis, we find both absolute and conditional convergence in all ten year periods from 1911 to 1993 except in the 20s and 80s. We find no convergence whatsoever in the 20s and only conditional convergence in the 80s. Analysing counties' interdependence, we find that counties are tied together such that growth in one county will have a significant impact on its neighbours. Further, we find that the regional cost of housing affects counties' demographic composition and, through this mechanism, growth in per capita income.

In the fifth and final essay we analyse how neglecting seasonal unit roots and vector ARMA modelling affect forecasts. We study the flow of monthly tourism flows into Sweden. The main conclusion is that the Box and Jenkins approach, taking a 12th difference to make the series stationary, is at least as good as the much more demanding route of analysing seasonal unit roots. In a second step, we investigate potential gains in using joint modelling techniques when making forecasts. We utilise other tourism series in order to improve the forecasts. The results are mixed. The results depend on what evaluation criteria we choose. In summary, find the Box and Jenkins approach to stand up well against more advanced techniques.

The Thesis consists of this introduction and the following essays. The essays will be referred to according to their title or number in brackets.

[1] Gustavsson, P., Hansson, P., and Lundberg, L. 1997. Technical Progress, Capital Accumulation and Changing International Competitiveness. In: Fagerberg, J. et al (Eds.), Technology and International Trade. Edward Elgar, Cheltenham, 20-37.

[2] Gustavsson, P., Hansson, P., and Lundberg, L. 1999. Technology, Resource Endowments and International Competitiveness. European Economic Review, 126(43), 1501-1530.

[3] Gustavsson, P. 2001. The Dynamics of European Industrial Structure. Mimeo, FIEF, Sweden.

[4] Gustavsson, P., and Persson, J. 2001. Convergence, Prices and Geography: An empirical Study of the Swedish Counties 1911-1993. Mimeo, FIEF, Sweden.

[5] Gustavsson, P., and Nordström, J. 1999. The Impact of Seasonal Unit Roots and Vector ARMA Modelling on Forecasting Monthly Tourism Flows. FIEF Working Paper: 150. Forthcoming in Tourism Economics, June 2001.

Essay 1*

* Co-authored with Pär Hansson and Lars Lundberg (FIEF). Published in: Fagerberg, J. et al (Eds.), Technology and International Trade. Edward Elgar, Cheltenham, 20-37.

Technical Progress, Capital Accumulation and Changing International Competitiveness[1]

Patrik Gustavsson, Pär Hansson, and Lars Lundberg

1. Introduction

This paper attempts to evaluate the role of differences in rates of resource accumulation between countries and different rates of technical progress as determinants of changes in the industrial patterns of comparative advantage, international competitiveness and specialization within manufacturing among OECD countries. Thus we attempt to combine two paradigms from trade theory, namely the technology or Ricardian view, and the factor proportions or Heckscher-Ohlin[2] explanations of changes in trade patterns.

Within the large empirical literature on the determinants of patterns of comparative advantage and specialization (for surveys see Deardorff 1984 and Leamer 1994), the main part analyses only the role of factor endowments. The factor proportion paradigm clearly cannot give a satisfactory explanation of all trade. In particular, it is not well suited for explaining intra-industry trade. Opinions on the value of factor endowments for explaining trade patterns are far from unanimous. While some authors argue that a generalized factor proportions model "seems to have stood up remarkably well to empirical scrutiny" (Deardorff op.cit.) and that it gives "a surprisingly good explanation of the main features of the trade data in terms of a relatively brief list of resource endowments" (Leamer 1984), others maintain that "the empirical validity of the endowment based theory of trade remains . . . very much subject to debate" (Dosi, Pavitt & Soete 1990).

The technology factor has been introduced into the empirical analysis of comparative advantage in various ways. Early studies used relative labour productivity data (MacDougall 1951, 1952) to explain countries' specialization according to the Ricardian model. Other studies found R&D intensity, in addition to a set of factor-proportion variables, to be positively related to US export performance (Gruber, Metha & Vernon 1967, Stern & Maskus 1981). Variables such as product age or income elasticity have also been used (Wells 1969, Hufbauer 1970, Finger 1975) as a proxy for various aspects of technology.

Introducing R&D intensity as a product or industry characteristic implies that R&D capacity is treated as just another resource (Dosi, Pavitt & Soete 1990). A different approach is to express competitiveness in terms of relative R&D intensity (Hughes 1986, Lundberg 1988). While R&D measures the input of resources in the production of new knowledge, patents may be a proxy for the output. Dosi, Pavitt & Soete (1990) found that countries' share of the number of patents in a product group was positively related to export shares. In a study by Amable & Verspagen (1995) changes in bilateral market shares among OECD countries were found to be positively related to relative (bilateral) R&D as well as the relative number of patents.

According to Deardorff (1984), the technology paradigm has "identified an important set of variables that can help to explain trade". A reasonable point of departure for an empirical study would be that both technology and factor proportions are likely to be important determinants of trade patterns, and therefore that both should be included in the set of explanatory variables. In this paper we will focus on total factor productivity as a measure of technology. Before proceeding to the empirical tests, however, we believe that it is necessary to specify exactly how these concepts are related to competitiveness and how they should be measured. In Section 2 we develop a simple model that leads to a set of testable hypotheses and regressions formulated in Section 3, which also contains a presentation of the data. The results are reported in Section 4 and Section 5 concludes.

2. Productivity, factor proportions and international specialization: the basic model

2.1 Factor prices, costs and goods prices

Assume n traded goods, $i = 1...n$, each produced by N_{ij} firms, $h = 1...N_{ij}$, in each of M countries, $j = 1...M$, with m factors of production, $k = 1...m$, which are perfectly mobile between sectors but immobile between countries. For the case of Cobb-Douglas technology, the production function of firm h in industry i and country j may be written as

$$q_{hij} = A_{ij} \prod_{k=1}^{m} x_{khij}^{\alpha_{ki}} \tag{2.1a}$$

where constant returns to scale implies that $\sum_{k=1}^{m} \alpha_{ki} = 1$. If all firms in industry i, country j are assumed to be identical we may write the aggregate production function for the ith industry in country j as

$$q_{ij} = A_{ij} \prod_{k=1}^{m} x_{kij}^{\alpha_{ki}} \tag{2.1b}$$

where q_{ij} is the output, and x_{kij} the amount of factor k used in the ith industry in country j. Technology in a particular industry is the same for all firms in a certain country and differs across countries only with a shift factor A_{ij} that corresponds to Hicks-neutral technical change. Factor shares α_{ki} are the same.

For the case of constant returns to scale and perfectly competitive factor markets, we derive the cost function dual of the Cobb-Douglas function by cost minimization:[3]

$$Z_{ij}(w,q) = A_{ij}^{-1} \prod_{k=1}^{m} \alpha_{ki}^{-\alpha_{ki}} w_{kj}^{\alpha_{ki}} q_{ij} \tag{2.2a}$$

where w_{kj} is the price of factor k in country j.

Let us now introduce economies of scale at the firm level and abandon the assumption of perfect competition. If the production function is assumed to be homothetic, we may write the unit cost function[4] as

$$c(w,q_{hij}) = A_{ij}^{-1} q_{hij}^{-\varepsilon_i} \prod_{k=1}^{m} \alpha_{ki}^{-\alpha_{ki}} w_{kj}^{-\alpha_{ki}} \tag{2.2b}$$

where ε_i is a measure of scale economies in the ith industry (we assume $\varepsilon_i > 0$).

Perfect competition in the product market ensures that prices equal unit costs. However, this result will also hold for the case of monopolistic competition with free entry:

$$p_{ij} = c_{ij}(w, q_{hij}) = G_i A_{ij}^{-1} q_{hij}^{-\varepsilon_i} w_{mj} \prod_{k=1}^{m-1} \left(\frac{w_{kj}}{w_{mj}} \right)^{\alpha_{ki}} = G_i A_{ij}^{-1} q_{hij}^{-\varepsilon_i} w_{mj} \prod_{k=1}^{m-1} \omega_{kj}^{\alpha_{ki}} \tag{2.3}$$

where $G_i = \prod_{k=1}^{m} \alpha_{ki}^{-\alpha_{ki}}$ and ω_{kj} is the relative price of factor k in terms of factor m.

Consider now a particular country j versus the rest of the world w. Assume that factor prices are not equalized and that there are no transport costs. The unit cost, and thus the price in all markets, for the ith good produced in j, relative to the cost and price of the same good produced in the rest of the world, will then be

$$\frac{p_{ij}}{p_{iw}} = \frac{w_{mj}}{w_{mw}} \frac{A_{iw}}{A_{ij}} \frac{q_{hiw}^{-\varepsilon_i}}{q_{hij}^{-\varepsilon_i}} \prod_{k=1}^{m-1} \left(\frac{\omega_{kj}}{\omega_{kw}} \right)^{\alpha_{ki}} \tag{2.4}$$

Let us choose the average world market unit cost and price for the ith product, average world technology, average firm size and the average world factor price ratios as standards of reference. We define

$$\xi_{ij} = \frac{p_{ij}}{p_{iw}} \quad T_{ij} = \frac{A_{ij}}{A_{iw}} \qquad W_{kj} = \frac{\omega_{kj}}{\omega_{kw}} \qquad \phi_{ij} = \frac{q_{hij}}{q_{hiw}}$$

as the relative price of the ith good produced in country j, the productivity advantage (disadvantage) of country j in the ith industry, the relative price of factor k in country j and the relative firm size in the ith industry in country j. The price of the products of all firms in the ith industry in country j, relative to the price charged by foreign firms in the same industry, is then

$$\xi_{ij} = B_j T_{ij}^{-1} \phi_{ij}^{\varepsilon_i} \prod_{k=1}^{m-1} W_{kj}^{\alpha_{ki}} \tag{2.5}$$

where $B_j = w_{mj} / w_{mw}$ (a country constant). Thus, if factor k is relatively expensive in country j ($W_{kj} > 1$) then the unit cost of good i in j relative to the cost in the rest of the world will be higher the more intensive the production of i in the use of factor k, i.e. the larger α_{ki}.[5] In addition, the unit cost will be lower the greater the productivity advantage of country j in the ith industry ($A_{ij} > A_{iw}$) and the larger the firms of country j in industry i relative to the rest of the world.

2.2 Demand

Consumer demand is assumed to be determined by a Spence-Dixit-Stiglitz (S-D-S) utility function, identical for all consumers and all countries. Let products of firms in the ith industry be differentiated in such a way that the elasticity of substitution for any pair of firms -- domestic or foreign -- is the same. Since all firms in the ith industry in a particular country are identical, and thus charge the same price, we may aggregate the demand for the output of all firms in each country in a particular industry. The analysis may then proceed as if products were differentiated only with respect to country of origin ($j = 1 \ldots N$).[6] If the products of all firms in the *ith* industry in country *j* are treated as an aggregate, the S-D-S function gives the utility of the representative consumer as

$$U = \prod_{i=1}^{n}\left(\sum_{j=1}^{M} C_{ij}^{b_i}\right)^{\frac{a_i}{b_i}} \qquad \sum_{i=1}^{n}\frac{a_i}{b_i} = 1 \tag{2.6}$$

where C_{ij} denotes consumption of the "aggregate product" in the *ith* industry produced in country *j*.

From (2.6) we can derive the demand for the *ith* good produced in country *j* in any market *g*, and thus the imports of good *i* from *j* to *g*.[7] Its demand will depend only on its relative price and total income in *g*:

$$C_{ijg} = \frac{p_{ij}^{-\sigma_i}}{\sum_{j=1}^{N} p_{ij}^{1-\sigma_i}}\frac{a_i}{b_i}Y_g = \left[\frac{p_{ij}}{p_{iw}}\right]^{-\sigma_i}\frac{a_i}{b_i}Y_g = \xi_{ij}^{-\sigma_i}\frac{a_i}{b_i}Y_g \tag{2.7}$$

where $\sigma_i = 1/(1-b_i)$ is the elasticity of substitution among products in the *ith* industry, Y_g aggregate real income in *g* (where the deflator is the price index for all goods) and p_{iw} is an aggregate price index for all products in the *ith* industry.[8]

2.3 The coefficient of specialization

Consider now a particular country's trade with the rest of the world. A measure of international competitiveness, specialization and net exports in the ith industry in country *j* is given by the coefficient of specialization, defined as the ratio of domestic production in the ith industry to domestic consumption of the *ith* good, including imports:

$$r_{ij} = \frac{Q_{ij}}{C_{ij}} = \frac{C_{ij} + X_{ijw} - X_{iwj}}{C_{ij}} \qquad (2.8)$$

where X_{ijw} is the exports of good i from country j, X_{iwj} is imports and Q_{ij} is gross production.[9]

By inserting (2.7) into (2.8) we obtain

$$r_{ij} = 1 + \frac{[\xi_{ij}^{-\sigma_i} Y_w - \{Y_j - \xi_{ij}^{-\sigma_i} Y_j\}]}{Y_j} = \xi_{ij}^{-\sigma_i}[(Y_w / Y_j) + 1] \qquad (2.9)$$

Inserting the expression for the relative unit cost and price from (2.5) finally gives

$$r_{ij} = \left[B_j T_{ij}^{-1} \phi_{ij}^{\varepsilon_i} \prod_{k=1}^{m-1} W_{kj}^{\alpha_{ik}} \right]^{-\sigma_i} F_j \qquad (2.10)$$

where B_j and F_j are country specific constants. Re-writing (2.10) in logarithms we have

$$\ln r_{ij} = (-\sigma_i \ln B_j + \ln F_j) + \sigma_i \ln T_{ij} + \sigma_i \varepsilon_i \ln \phi_{ij} - \sum_{k=1}^{m-1} \sigma_i \alpha_{ki} \ln W_{kj} \qquad (2.11)$$

where the first term is a country-specific constant. Thus the value of the specialization coefficient for a given country in any good/industry is low for goods intensively using the country's expensive (and scarce) factors (i.e. factor intensity α_{ki} and relative factor cost W_{kj} are both high), where the country has a productivity disadvantage (T_{ij} is low) and where firms are relatively small. These mechanisms work through the relative unit cost and price. Moreover, the effect of a given cost difference is larger the higher the elasticity of substitution among products σ_i in the ith industry.[10]

By differentiating (2.13) we obtain an equation for the rates of change:

$$\hat{r}_{ij} = \sigma_i \hat{T}_{ij} + \sigma_i \varepsilon_i \hat{\phi}_{ij} - \sum_{k=1}^{m-1} \sigma_i \alpha_{ki} \hat{W}_{kj} \qquad (2.12)$$

where $\hat{r}_{ij} = (dr_{ij} / r_{ij} dt)$ and correspondingly for $\hat{T}_{ij}$, $\hat{W}_{kj}$ and $\hat{\phi}_{ij}$.

3. Data and econometric models

The hypotheses emerging from the model discussion can be briefly summarized as follows:

The specialization coefficient of the ith industry in country j will be determined, first, by a combination of industries' resource requirements and countries' resource endowments. Countries will specialize on industries intensively using their cheap resources. This effect is represented in a log-linear equation by an interaction term $\sigma_i \alpha_{ki} \ln W_{jk}$, where α_{ki} is the share of k of total factor costs in the ith industry, and W_{kj} is the relative price of factor k in country j compared to the rest of the world. The effect of a given cost difference on market shares and specialization is determined by σ_i, the elasticity of substitution among products from different firms within the ith industry.

Surveys of empirical work (e.g. Leamer 1994 and Deardorff 1984) conclude that natural resources affect industrial localization, not only of extractive industries but also of processing industries. In addition, both human and physical capital have been found to be important. In principle, one should include resources which are internationally immobile, where endowments differ among countries, and requirements differ among industries. In this study, we have included interaction variables measuring country endowments, in combination with industry requirements, of

- forest land per worker/cost share of roundwood
- arable land per capita/food industry (a dummy)
- electrical energy[11]
- physical capital
- human capital or skilled labour, measured by formal education.

In the standard Heckscher-Ohlin multi-sector and multi-factor model, it can be shown (Ethier 1984) that factor prices in autarky are negatively correlated with factor abundance, so that abundant factors, as well as goods intensively using these factors, tend to be cheap; thus, such goods will be exported. Formally this requires homothetic and identical consumer demand, perfect competition and that goods outnumber factors. In this paper we use this equivalence of factor endowments and factor prices.

We measure countries' resource endowments in physical terms (i.e. aggregate capital stock per worker, proportion of labour force with higher education, etc.) rather than resource prices, since comparable data for prices are not available. Moreover, the variables measuring industries' factor intensities are also in physical terms, i.e. capital intensity is measured by the stock of machinery and equipment per worker, rather than cost shares. One reason for this choice is that factor rewards, especially profits, are probably more affected by spurious short term variability than quantities. All industry characteristics, i.e. capital, energy and roundwood intensities, are measured using Swedish data and thus assumed to be the same across countries.

Thus the hypothesis may be reformulated as follows: countries will, on average, specialize in industries intensively using their abundant factor.

The term $\sigma_i \alpha_{ki} \ln W_{kj}$ is replaced in (2.11) by $\sigma_i v_{ki} \ln V_{kj}$, where V_{kj} is the relative endowment of resource *k* (e.g. total stock of physical capital per worker), proportion of skilled workers of the labor force or forest (arable) land per worker in country *j*, and v_{ki} is the factor *k* intensity (e.g. machinery and equipment per worker) in the ith industry.

Second, specialization will also be determined by the level of productivity or efficiency in an industry relative to its competitors (T_{ijt}). According to the model the relevant concept here is total factor productivity, TFP, defined as the ratio of output to a weighted sum of the inputs used. For the case of a Cobb-Douglas production function, the relevant input weights are the cost shares, which corresponds to the output elasticities α_{ki} in (2.1a).

Third, specialization is affected by relative firm size ϕ_{ij} : the larger the firms, the lower will be costs and prices. The effect on costs of a given size difference depends on the extent of scale economies in the industry ε_i. Finally, the effect of a given cost and price difference, caused by factor proportions, technology or firm size, on specialization is larger the higher is σ_i, the elasticity of substitution among products of different firms in the ith industry. The Appendix describes the definitions, sources and calculations used to obtain T_{ijt}, $\hat{T}_{ij}$, ϕ_{ij}, ε_i and σ_i in detail.[12]

For nine industries[13] in nine OECD countries we have estimated two basic equations, one for 1987/89 levels of r_{ij} :

$$\ln r_{ijt} = \beta_0 + \sum_{j=11}^{N-1} \beta_{0j} D_j + \sum_{i=1}^{n-1} \beta_{0i} D_i + \beta_1 \ln T_{ijt} + \sum_{k=1}^{m-1} \beta_{2k} v_{ki} \ln V_{kjt} + \beta_3 \varepsilon_i \ln \phi_{ij} + \mu_{ijt} \tag{3.1}$$

the other for changes from 1970/72 to 1987/89:

$$\hat{r}_{ij} = \beta_0 + \sum_{j=1}^{N-1} \beta_{0j} D_j + \sum_{i=1}^{n-1} \beta_{0i} D_i + \beta_1 \hat{T}_{ij} + \sum_{k=1}^{m-1} \beta_{2k} v_{ki} \hat{V}_{jk} + \mu_{ij} \tag{3.2}$$

where μ_{ij} and μ_{ijt} are error terms. Since endowments of forest and arable land do not change they are excluded from (3.2); so too is the plant size variable ϕ_{ij} , since data for changes are not available. In addition, we have attempted to allow for industry differences in the degree of substitution between firms' products by estimating a version of (3.1) and (3.2) where all of the independent variables (except the dummy variables) have been multiplied by a measure of σ_i, the elasticity of substitution among differentiated products within the ith industry (cf. 2.11 and 2.12; see Appendix).

The coefficients β_1 for relative TFP level T_{ijt} and relative TFP growth rate $\hat{T}_{ij}$ are expected to be positive: other things being equal, the higher the level (rate of growth) of TFP in the ith industry in country j relative to the rest of the world, the lower the (increase of the) unit cost, and the higher the (increase of the) coefficient of specialization. The factor endowments coefficients β_{2k} will be positive; specialization coefficients will be higher in industries intensive in abundant factors, and increase in industries intensive in factors with a high rate of growth of domestic supply. Finally, by utilizing economies of scale larger firms will be more competitive ($\beta_3 > 0$).

The regression equations contain a number of country and industry intercept dummy variables, D_j and D_i. The country dummies can be motivated by the variation in trade balance in manufactures, surplus countries having a tendency to higher specialization coefficients in all industries. Since the countries in the analysis are all "rich" by global standards, all tend to have surpluses (deficits) with "poor" countries in the same type of goods (cf. computers vs. textiles). The same argument holds for the second equation where dummies represent common trends.

The sources, measurement and definition of the variables are presented in detail in the Appendix.

4. Empirical results

4.1 Factor endowments and specialization

The results in *Table 1* indicate that natural resources, represented by forest land and arable land, as well as domestic supplies of electrical energy, influence countries' specialization patterns. The coefficients of the corresponding interaction variables are mostly positive and significant. This holds also for human capital, but only in robust regressions; thus this result is somewhat sensitive to the treatment of extreme observations. Physical capital does not seem to have any link whatsoever to specialization.

Table 1 Determinants of the pattern of specialization 1987/89 in OECD countries

Variable	(i)	(ii)	(iii)	(iv)
Total factor Productivity	0.144 (1.97)* /2.29/** [1.13]	0.114 (1.55) /2.15/** [1.02]	−0.039 (−0.53) /−0.98/ [0.51]	0.006 (0.13) /0.19/ [0.80]
Physical capital		-9.16×10^{-8} (−0.76) /−1.08/ [−1.12]	1.67×10^{-6} (0.43) /0.60/ [0.69]	1.18×10^{-6} (0.71) /0.92/ [0.89]
Human capital		0.649 (1.21) /1.60/ [1.35]	8.750 (0.92) /1.02/ [3.08]***	6.646 (1.54) /1.91/* [2.29]***
Energy		0.001 (2.28)** /3.69/*** [3.44]***	0.019 (2.72)*** /3.58/*** [3.11]***	0.006 (1.87)* /2.30/** [1.95]*
Forest land		2.78×10^{-5} (1.75)* /1.70/* [3.94]***	2.11×10^{-5} (1.31) /1.64/ [4.89]***	1.79×10^{-5} (1.85)* /2.38/** [5.54]***
Arable land		−0.063 (−1.09) /−1.97/* [−0.99]	0.101 (1.58) /2.05/** [2.02]**	0.053 (1.55) /2.13/** [2.22]**
Plant size		0.180 (2.41)** /2.98/*** [2.73]***	0.198 (2.48)** /2.86/*** [2.28]***	0.094 (2.50)** /2.77/*** [2.22]**
Constant	−0.059	−0.180	−8.220	−1.085
Country dummies			yes	yes
Industry dummies			yes	yes
R^2	0.036	0.161	0.559	0.558
Observations	78	70	70	70

Note: The table shows the estimated regression coefficients and their t values. Numbers in parentheses ( ) give t-values in OLS regressions, slashes / / White's (1980) t-statistics corrected for heteroscedasticity by computing Huber standard errors, and square brackets [ ] t-values in robust regressions, where extreme observations are given lower weights. The parameter estimates in robust regressions differ somewhat from those in OLS regressions but are not presented. The symbol * indicates that the estimated coefficient is significant at the 10 % level, ** at the 5 % level , and *** at the 1 % level. For the dummy variables we report the probability that all coefficients for the group equal zero. In equation (iv) all dependent variables have been multiplied by a measure of the intra-industry elasticity of substitution (σ_i in 2.11).

Table 2 Determinants of changes in the pattern of specialization 1970/72 - 1987/89 in OECD countries

Variable	(i)	(ii)	(iii)	(iv)
Total factor Productivity Growth	0.156 (1.90)* /2.32/** [1.75]*	0.093 (1.18) /1.68/* [1.10]	0.127 (1.96)* /2.17/** [3.85]***	0.070 (2.07)** /2.41/** [4.42]***
Physical capital Growth		9.56×10^{-7} (1.73)* /1.87/* [1.50]	-1.14×10^{-6} (−0.89) /−0.88/ [−1.78]*	-8.40×10^{-7} (−1.85)* /−2.29/** [−3.06]***
Human capital Growth		−0.129 (−1.47) /−1.47/ [−1.09]	0.865 (2.93)*** /2.32/** [0.84]	0.315 (3.54)*** /3.35/*** [4.18]***
Growth of energy Supply		0.006 (2.33)** /3.17/*** [2.34]**	−0.005 (−1.06) /−1.40/ [−0.82]	−0.002 (−1.18) /−1.56/ [−1.46]
Constant	−0.030	−0.076	−0.441	−0.055
Country dummies			yes	Yes
Industry dummies			yes	Yes
$\bar{R}^2$	0.033	0.170	0.590	0.615
Observations	78	78	78	78

Note: see *Table 1*. For forest land, arable land and plant size no time series data were available: thus these variables are not included here. Column (iv) gives the estimated coefficients when all variables are multiplied by the elasticity of substitution variable.

The inclusion of country and industry dummy variables in columns (iii) and (iv) results in a highly significant addition to the explanatory value of the regression. Countries with export surplus in manufactures, such as Japan and Germany, tend to show positive coefficients, while for deficit countries such as Norway coefficients are mostly negative.

Table 2 shows that countries where the domestic supply of skilled labour did increase at a high rate have increased their specialization in skill-intensive goods.[14] Thus the results indicate that the stock of human capital and its rate of increase are important determinants of levels and changes of international competitiveness. The growth of the stock of machinery and equipment and the increase in the capacity for energy production do not seem to be important in this respect; in fact, the physical capital variable turns out to have the wrong sign.[15]

Furthermore, as shown by *Table 1*, specialization coefficients seem to increase with relative plant size in industries where economies of scale of various types are common. This is indicated by the strongly significant positive coefficient for the variable ϕ_{ij}.[16]

Finally, columns (iii) and (iv) show the results of an attempt to take account of the degree of intra-industry product differentiation, by adjusting the independent variables for differences in the elasticity of substitution among products. This seems to improve the performance of the model somewhat, especially in the equation for changes in *Table 2*, in the sense that the significance of certain variables tends to increase.

4.2 The role of total factor productivity for international competitiveness

On the issue of the importance of technology for competitiveness and specialization, Tables 1 and 2 seem to lead to radically different conclusions. According to *Table 1*, column (i), the relative TFP level seems to have a positive effect on specialization, which disappears when we allow for country and industry fixed effects (columns iii and iv). The poor performance of the technology variable could be explained by measurement errors. Since the TFP indices have to be deflated to a common currency, the choice of deflator -- here PPP-adjusted exchange rates in 1985 -- is bound to have a substantial effect on the results; other ways of transforming the indices would probably give widely different results.[17]

That the data for TFP levels might be less reliable than those for changes in 1970-89 (which are calculated from volume changes in fixed prices in domestic currency) is indicated by the results in *Table 2*.[18] In particular, column (iv) shows that the technology effect becomes strongly significant after taking account of varying elasticities of substitution. This result is not affected by adjustment for heteroscedasticity or the treatment of extreme observations.[19]

Our results show that international competitiveness has improved in industries and countries where the rate of increase of total factor productivity was high relative to the OECD average. Thus the hypothesis about the central role of technical progress for competitiveness is confirmed. However, the results also point to the role of changing endowments of human capital. Countries where the average level of education (mean years of schooling) did increase tended to increase their specialization on human-capital-intensive goods.

5. Concluding comments

In this paper we attempt to evaluate two central paradigms in international trade theory concerning the determinants of comparative advantage and specialization, namely technology versus factor proportions. Our main conclusion is that both sets of variables seem to be important. Factor endowments of countries, in combination with factor requirements of industries, seem to be significant determinants of trade and specialization. Different rates of factor accumulation -- in particular of human capital -- contribute to the explanation of changing specialization patterns. But so do differences in rates of technical progress.

In an empirical study covering nine OECD countries and nine industry groups we find that countries tended to increase their specialization in the period 1970-89 in industries where total factor productivity had been growing at a high rate compared to competitors. We also found that specialization increased in human-capital-intensive goods in countries with a high rate of growth of the national supply of skilled labour. These results are reinforced by allowing for country and industry specific fixed effects and different degrees of homogeneity among products within industries. For specialization levels, however, the technology variable performed poorly, whereas factor proportions -- especially natural resources -- were significant. This result may be due to measurement problems.

This paper cannot, of course, give a definite answer to the question of whether technology or factor proportions is the single most important explanation for competitiveness and trade patterns. One reason for this is that our analysis is likely to omit some of the effects of improved technology. In principle, an innovation resulting in a new and better product, which will command a higher price, should be reflected in an increase in TFP. In practice, however, this effect is often likely to be deflated away, to the extent that price indices are not properly adjusted for quality changes. We may, however, conclude that both explanations are important, and that our results indicate that analyses of changing patterns of international competitiveness and specialization which focus only on one of the paradigms, omitting the other, may be seriously misleading.

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Appendix Variables: definitions, measurement and sources

Coefficient of specialization: r_{ijt}

$$r_{ijt} = \frac{Q_{ijt}}{C_{ijt}} = \frac{Q_{ijt}}{Q_{ijt} + X_{iwjt} - X_{ijwt}}$$

Q_{ijt} production (gross output), industry i, country j, time t

C_{ijt} consumption, industry i, country j, time t

X_{iwjt} import, industry i, from the whole world w to country j, time t

X_{ijwt} export, industry i, from country j to the whole world w, time t
$t = 1, 2$; 1 = average 1970-72 and 2 = average 1987-89

Source: OECD (1994a).

Total factor productivity variables: $T_{ijt} = \ln(A_{ijt} / A_{iwt})$ *and* $\hat{T}_{ij} = \hat{A}_{ij} - \hat{A}_{iw}$

$$\ln A_{ijt} = \ln q^{*}_{ijt} - \alpha_i \ln L_{ijt} - (1-\alpha_i)K^{*}_{ijt}$$

A_{ijt} total factor productivity, industry i, country j, time t
q^{*}_{ijt} value added, industry i, country j, time t, US dollar 1985 PPP, 1985 prices
K^{*}_{ijt} capital stock, industry i, country j, time t, US dollar 1985 PPP, 1985 prices
L_{ijt} employment, industry i, country j, time t
α_i output elasticity of labor, industry i; measured as wages' share of value added

A_{ijt} / A_{iwt} relative productivity

A_{iwt} average total factor productivity in the studied countries

$\hat{A}_{ij} - \hat{A}_{iw}$ relative productivity growth

$\hat{A}_{ij} = \ln A_{ij2} - \ln A_{ij1}$
$\hat{A}_{iw} = \ln A_{iw2} - \ln A_{iw1}$

Source: OECD (1993a).

Economies of scale and firm size variable: $\varepsilon_i \phi_{ij} = \varepsilon_i(\ln s_{ij} - \ln s_{iw})$

ε_i dummy variable for industries with large economies of scale, according to a ranking made by Pratten (1988) Table 5.3b
s_{ij} average number of employees per establishment 1988, country j, industry i.

s_{iw} average number of employees per establishment 1988, all countries, industry *i*.
Source: OECD (1992).

Physical capital interaction variables: $k_i \ln k_{j2}$ *and* $k_i \hat{k}_j$

k_i capital stock per employee, industry *i*, USA 1988.

k_{j2} capital stock per employee in manufacturing, country *j*, average 1987/89.

$\hat{k}_j$ $\ln k_{j2} - \ln k_{j1}$

Source: OECD (1993a).

Human capital interaction variables: $h_i \ln h_j$ *and* $h_i^* \hat{h}_j^*$

h_i proportion of employees in industry *i* with a university degree in engineering (3 years or more), Sweden, 1990. Source: SCB Regional Labor Statistics.

h_j number of graduates in science and engineering per 100.000 of population aged 25-35, country *j*, 1991. Source: OECD (1994b).

h_i^* average number of years of schooling in industry *i*, Sweden 1990. Source: SCB Regional Labor Statistics

$\hat{h}_j^*$ $\ln h_{j85}^* - \ln h_{j70}^*$ increase in average number of years of schooling of labor force in country *j* from 1970 to 1985. Source: Barro & Lee (1993)

Interaction variable for forest land: $t_i \ln t_j$

t_i input of roundwood SEK per 10 000 SEK output, industry *i*, Sweden, 1985. Source: SCB Input-output table for Sweden 1985.

t_j forest land per worker, country *j*, 1990. Source: SCB (1993).

Energy interaction variable: $e_i \ln e_j$

e_i cost of electrical power per employee, industry i, Sweden, 1987. Source: SOS Manufacturing 1987.

e_j production of electrical power per capita 1991, country j. Source: SCB (1994).

Interaction for arable land: $a_i \ln a_j$

a_i dummy variable for industry 31 (food)

a_j hectare arable land per capita 1991. Source: SCB (1994).

Elasticity of substitution: σ_i

In the theoretical model in Section 2, the elasticity of substitution between different products in an industry equals the elasticity of demand in the case of large number of products. Such elasticities have been estimated for industries at the 6-digit level of SNI in Sweden 1983 (Hansson 1989). From those estimates we have constructed consumption weighted elasticities of substitution at the ISIC 2-digit level.

Table A1 Industries and countries in the study

ISIC	Industry	Country
31	Food	United States
32	Textile	Canada
33	Wood	Japan
34	Paper	Germany
35	Chemical	France
36	Non-Metallic	United Kingdom
37	Basic metal	Denmark
38	Machinery	Norway
39	Other	Sweden

Data sources

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SCB, SOS Manufacturing Part I, 1985 och 1986.

SCB, Input-Output Table for Sweden 1985.

SCB Regional Labour Statistics, Unpublished data on employees by industry and level of education.

Endnotes

[1]We are grateful to Steven Globerman and other participants at the conference at Leangkollen for comments, and to the Swedish Council for Research in the Humanities and Social Sciences for financial support.

[2] There is, of course, not necessarily an unambiguous distinction between the two paradigms, neither in theory nor in empirical studies. Knowledge or technology may be treated either as a variable in the production function, or as embodied in the parameters of the function.

[3] See e.g. Berndt (1991) pp.68-69.

[4] Helpman & Krugman (1985) p.143; the particular form of equation 2.2b is obtained if we introduce increasing returns to the production function in 2.1a by raising the right-hand side (excluding the A_{ij} term) to the power of $\varepsilon_i > 0$.

[5] From the first order condition of profit maximization we know that the value of the mth factor's marginal product equals the factor price of m. With Cobb-Douglas production technology this implies that

$$\frac{\alpha_{ki} x_{mij}}{\alpha_{mi} x_{kij}} = \frac{w_{kj}}{w_{mj}}$$

which means that the k intensity in the ith sector in country j is

$$f_{kij} = (x_{kij} / x_{mij}) = \alpha_{mi}^{-1} \alpha_{ki} \omega_{kj}^{-1}$$

Hence, the k intensity -- units of k per unit of m -- in country j is a function of the cost share of k in industry i (equal internationally) and the national relative factor price (same in all industries).

[6] Armington (1969).

[7] See e.g. Helpman & Krugman (1985) pp.118-119.

[8] The utility function in (2.6) implies that the dual aggregate price index for all products produced in the ith industry is (Varian (1992) p.112)

$$p_{iw} = \left[\sum_{j=1}^{N} p_{ij}^{1-\sigma_i} \right]^{\frac{1}{1-\sigma_i}}$$

[9] The r measure is thus equivalent to the net export ratio.

[10] The model assumes that trading costs equal zero. Otherwise, the r_{ij} :s will approach one when tariffs or transport costs increase.

[11] A country's production of electrical energy may be treated as a "natural" resource to the extent that it is based on, for example hydroelectric power. However, energy-intensive production, while historically based on cost advantages of abundant and cheap hydro-electric capacity, may over time acquire a technological advantage that creates the base for future competitiveness. This may lead to investment in "non-natural energy production capacity such as nuclear power. Thus the causal interpretation of a correlation between energy production and the size of the energy-intensive industry sector may be ambiguous.

[12] The value of r would also be affected by transport costs, tariffs and other barriers to trade: the higher and more restrictive these are the more r will approach one. However, no comprehensive measure of trading costs was available for the econometric analysis.

[13] In principle one would prefer to do the analysis at a rather disaggregated industry level. In practice, however, the aggregation level is given by the availability of capital stock data.

[14] The measure of skilled labour is not the same in Tables 1 and 2. In Table 1 the human capital interaction variable is based on the proportion of employees with a university

degree in scientific, mathematical, computing or engineering subjects in employment in the ith industry, respectively of the age group 25-35 years in the population of the jth country. Since these data are not available over time we have used an interaction variable in Table 2 calculated as mean years of schooling of employees in the ith industry, multiplied by the increase in mean years of schooling of the total labour force of the jth country.

[15] The variables measuring human and physical capital, as well as energy and plant size, are positively correlated; thus the estimates for each of these are affected by exclusion of the others.

[16] The fact that countries' national industrial statistics use different size criteria for inclusion will produce some measurement errors; this, however, will not affect industries with large economies of scale where there are no small plants. The plant size coefficient might be biased if competitiveness leads to larger plants, i.e if there is simultaneity. A Hausman test indicates that plant size is uncorrelated with the error term in equation (iv) table 1.

[17] However, in a study of bilateral intra-Nordic trade Torstensson (forthcoming) finds a positive effect of technology advantages measured as relative levels of labour productivity.

[18] The same result -- that the relationship between TFP growth and changes in comparative advantage was much stronger than that between levels of relative TFP and export patterns -- was found by Dollar & Wolff (1993).

[19] Since the dummy variables can be motivated both by statistical (F-tests) and economic (as proxies for trade deficits/surpluses) criteria we chose equation (iv) as the preferred one.

Essay 2*

* Co-authored with Pär Hansson and Lars Lundberg (FIEF). Published in: European Economic Review. 1999. Vol 43(8) 1501-1530.

TECHNOLOGY, RESOURCE ENDOWMENTS AND INTERNATIONAL COMPETITIVENESS*

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Abstract

The paper evaluates the impact of technology together with resource endowments, factor prices and economies of scale on international competitiveness in OECD countries. Knowledge capital stocks are obtained by cumulating R&D expenditure. Results show that competitiveness is determined not only by the R&D activity of the representative firm, but also by total R&D in the domestic industry as well as economy wide stocks of knowledge, indicating the presence of local externalities. Competitiveness is also affected by factor prices and resource endowments as well as scale economies and learning by doing. Further results points to the importance of economies of scale in R&D internal to the firm, of the degree of openness for the capacity to utilize global spillovers and of investment for introduction of embodied technical progress. Finally, the R&D impact is higher in high- and medium- than in low-tech industries.

JEL classification: F12, F14, O32
Keywords: international competitiveness, technology gap, R&D stocks, technology spillovers

* **Acknowledgements**: This paper is part of a research project, Technology, Economic Integration and Social Cohesion, within the TSER programme of European Commission. Financial support from the Swedish Council for Research in the Humanities and Social Sciences, as well as helpful comments from an anonymous referee, are gratefully acknowledged.

1. Introduction

This paper attempts to evaluate the role of technology in combination with domestic resource prices and endowments and economies of scale as determinants of industrial patterns of comparative advantage, international competitiveness and specialization within manufacturing among OECD countries. Thus we attempt to combine two paradigms from trade theory, namely the technology or Ricardian view, and the factor proportions or Heckscher-Ohlin explanations of trade patterns.

Within the large empirical literature on the determinants of patterns of comparative advantage and specialization (for surveys see Deardorff 1984 and Leamer and Levinsohn 1995), most studies treat the role of factor endowments. Technology has been introduced into the empirical analysis of comparative advantage in various ways. Early studies used relative labor productivity data (MacDougall 1951, 1952) to explain countries' specialization. Other studies found R&D intensity, in addition to a set of factor proportions variables, to be positively related to US export performance (Gruber, Metha and Vernon 1967, Stern and Maskus 1981). Variables like product age or income elasticity have been used (Wells 1969, Hufbauer 1970, Finger 1975) to proxy various aspects of technology.

Introducing R&D intensity as a product characteristic, as in these studies, implies that R&D capacity is treated as just another resource. A more satisfactory approach, based on Posner's (1961) concept of technology gaps, is to explain competitiveness in terms of *relative* R&D intensity, where high values are assumed to result in better products and/or more efficient methods. On the macro level, differences in national R&D activity has been shown to influence export growth, i.e. *absolute* advantage, more than traditional measures of price competitiveness (Fagerberg 1988).

There is a growing literature on the role of technology for *comparative* advantage or *relative* international competitiveness, measured on the industry level by (gross) exports, export shares, revealed comparative advantage or net export shares of consumption (for a survey see Verspagen and Wakelin 1997). These studies use various proxies for technology. While R&D expenditure measures the input of resources in the production of new knowledge, patents or total factor productivity growth (TFP) may be proxies for the output.

Dosi, Pavitt and Soete (1990) found that countries' share of the number of patents in a product group was positively related to export shares. In a study by Amable and Verspagen (1995) changes in bilateral market shares among OECD countries were found to be positively related to relative (bilateral) R&D as well as the relative number of patents. Fagerberg (1997) found knowledge achieved by R&D as well as knowledge emerging in other industries and spread via goods' trade to be important for exports in a cross-industry/cross-country study. That relative rates of TFP growth seem to influence changes in comparative advantage has been demonstrated by Wolff (1997) and Gustavsson, Hansson and Lundberg (1997).

Most of these studies, however, do not explicitly include other potentially important variables such as factor endowments.[1] In this paper we want to do a comprehensive evaluation, based on an explicit theoretical model -- developed in order to give some structure to the empirical analysis -- of the role of technology, together with economies of scale and factor prices/factor endowments in combination with factor intensities, for costs, prices and thus for the competitiveness of firms and industries.

In the paper we attempt to evaluate the different sources of technology available to firms, such as learning, the stock of (firm specific) knowledge generated by own R&D cumulated over time, knowledge evolving in the rest of the industry and spread via local externalities, global technology spillovers and technical progress embodied in new capital goods. Moreover, we study if the impact on cost and competitiveness of a given increase in the R&D stock depends on firm size, i.e. if there are economies of scale in R&D internal to the firm,[2] and if the R&D impact differs between high- and low-tech industries.[3]

The paper is organized as follows. In section 2 we derive the impact of technology on costs, prices and world market shares -- i.e. "revealed" international competitiveness -- starting from a production function and the corresponding cost function.[4] This approach is basically the same as in

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[1] Some studies (e.g. Amable and Verspagen 1995 and Fagerberg 1997) introduce variables measuring price competitiveness, such as relative unit labor cost, the performance of which tends to be inferior to the "non-price competitivness" factors such as R&D and investment. However, in our view this is not equivalent to a test of the factor endowments approach.

[2] If the effect on efficiency of a firm's own research increases with the size of the total stock of knowledge in the industry there is a scale effect on the industry level, i.e. external to the firm.

[3] The results of Fagerberg (1997) indicate that the impact of R&D may differ among industries.

[4] Regarding the choice of model, we want to set up the simplest framework possible, linking technology, scale and factor prices to competitiveness, using assumptions on supply, demand and market form which are standard in the literature, and containing characteristics which we believe are empirically relevant, such as economies of scale

most studies of the impact of R&D on productivity (for a survey see Griliches 1995). Section 3 describes the data, including the industry and country pattern of the knowledge capital stocks constructed by summing R&D expenditure over time. Section 4 contains the results from the empirical analysis. Section 5 discusses some limitations of the analysis and section 6 concludes.

2. The model

2.1 Factor prices, costs, technology and goods prices

Assume n traded goods, $i = 1...n$, each produced by N_{ij} firms, $h = 1...N_{ij}$, in each of M countries, $j = 1...M$, with m factors of production, $k = 1...m$, which are perfectly mobile between sectors but immobile between countries. Each firm sells a differentiated product under monopolistic competition with free entry. For the case of a generalized Cobb-Douglas technology, the production function of firm h in industry i and country j may be written as[5]

$$q_{hij} = A_{hij} \prod_{k=1}^{m} x_{khij}^{\alpha_{ki}} \tag{2.1.1}$$

where returns to scale is given by

$$\mu_i = \sum_{k=1}^{m} \alpha_{ki} \tag{2.1.2}$$

Technology in a particular industry is the same for all firms in a certain country and differs across countries only with a shift factor A_{hij} that corresponds to Hicks-neutral technical change. The elasticities α_{ki} and the scale parameter μ_i are identical across countries.

For the case of perfectly competitive factor markets, we derive the unit cost function dual to the Cobb-Douglas function by cost minimization, following Berndt (1991, p. 68 ff.) to obtain:

and product differentiation. The model structure resembles the standard model outlined in Helpman and Krugman (1985), part III.

[5] Unless stated otherwise we suppress the time index.

$$\ln c_{hij} = \phi_i + \left(\frac{1-\mu_i}{\mu_i}\right)\ln q_{hij} - \mu_i^{-1}\ln A_{hij} +$$
$$+\sum_{k=1}^{m}\mu_i^{-1}\alpha_{ik}\ln w_{kj} \qquad (2.1.3)$$

If all firms in industry *i*, country *j* are identical, they will produce the same output at the same cost; the unit cost function for the industry ($\ln c_{ij}$) is then also given by (2.1.3).

Monopolistic competition with free entry ensures that prices equal unit costs. Consider now a particular country *j* versus the rest of the world *w*. Assume that factor prices are not equalized, that firm size may differ among countries in each industry and that there are no transport costs. The unit cost, and thus the price in all markets, for the *i*:th good produced in *j*, relative to the cost and price of the same good produced in the rest of the world, will then be

$$\ln p_{ij} - \ln p_{iw} = \left(\frac{1-\mu_i}{\mu_i}\right)(\ln q_{hij} - \ln q_{hiw}) - \mu_i^{-1}(\ln A_{hij} - \ln A_{hiw}) +$$
$$+\sum_{k=1}^{m}\mu_i^{-1}\alpha_{ki}(\ln w_{kj} - \ln w_{kw}) \qquad (2.1.4)$$

2.2 Demand

Consumer demand is assumed to be determined by a Spence-Dixit-Stiglitz (S-D-S) utility function, identical for all consumers and all countries. Let products of firms in the *i*:th industry be differentiated in such a way that the elasticity of substitution for any pair of firms -- domestic or foreign -- is the same. Since all firms in the *i*:th industry in a particular country are identical and charge the same price, we may aggregate across firms to obtain the demand for the output of each country in a particular industry. The analysis may then proceed as if products were differentiated only with respect to country of origin ($j = 1 \ldots M$) (Armington 1969). If the products of all firms in the *i*:th industry in country *j* are treated as an aggregate, the S-D-S function gives the utility of the representative consumer as

$$U = \prod_{i=1}^{n}\left(\sum_{j=1}^{M} D_{ij}^{b_i}\right)^{\frac{a_i}{b_i}} \qquad \sum_{i=1}^{n} a_i = 1 \qquad (2.2.1)$$

where D_{ij} denotes consumption of the "aggregate product" in the i:th industry produced in country j.

From (2.2.1) we derive the demand for the i:th good produced in country j in any market g, and thus the imports of good i from j to g (cf. Helpman and Krugman 1985, p. 118 ff.). Demand will depend only on relative price and total income in g:

$$D_{ijg} = \frac{p_{ij}^{-\sigma_i}}{\sum_{j=1}^{N} p_{ij}^{1-\sigma_i}} aY_g \qquad \sigma_i > 1 \tag{2.2.2a}$$

where $\sigma_i = 1/(1-b_i)$ is the elasticity of substitution among products in the i:th industry. Using the definitions of the CES price-index,

$$\sum_{j=1}^{N} p_{ij}^{1-\sigma_i} = p_{iw}^{1-\sigma} \tag{2.2.2b}$$

expenditure in g of good i imported from j is

$$C_{ijg} = p_{ij} D_{ijg} = \left[\frac{p_{ij}}{p_{iw}}\right]^{1-\sigma_i} a_i Y_g \tag{2.2.2c}$$

where Y_g is aggregate income in g and p_{iw} is an aggregate price index for all products in the i:th industry (Varian 1992, p. 112).

2.3 The coefficient of specialization

Consider now a particular country's trade with the rest of the world. A measure of international competitiveness, specialization and net exports in the i:th industry in country j is given by the coefficient of specialization, defined as the ratio of domestic production in the i:th industry to domestic consumption of the i:th good, including imports:

$$r_{ij} = \frac{Q_{ij}}{C_{ij}} = \frac{C_{ij} + X_{ijw} - X_{iwj}}{C_{ij}} \tag{2.3.1}$$

where X_{ijw} is the exports of good i from country j, X_{iwj} is imports and Q_{ij} is gross production; r equals the net export ratio plus one.

Inserting (2.2.2c) into (2.3.1), setting $X_{ijw} = C_{ijw}$ and $X_{iwj} = C_{iwj}$, we obtain

$$r_{ij} = \left[\frac{p_{ij}}{p_{iw}}\right]^{1-\sigma_i} [(Y_w / Y_j) + 1] \tag{2.3.2}$$

Inserting the expression (2.1.4) for the relative price into (2.3.2) and rewriting in log form gives

$$\ln r_{ij} = \ln F_j - \frac{(1-\sigma_i)}{\mu_i}(\ln A_{hij} - \ln A_{hiw}) + \frac{(1-\sigma_i)(1-\mu_i)}{\mu_i}(\ln q_{hij} - \ln q_{hiw})$$
$$+\frac{(1-\sigma_i)}{\mu_i}\sum_{k=1}^{m}\alpha_{ki}(\ln w_{kj} - \ln w_{kw}) \qquad (2.3.3)$$

where the first term is a country-specific constant. Thus the value of the specialization coefficient for a given country in any good/industry will be low for goods intensively using the country's expensive (and scarce) factors (i.e. factor intensity α_{ki} and factor price w_{kj} are both high), where the country has a productivity disadvantage (A_{hij} is low) and where firms are relatively small (reflecting increasing returns to scale). These mechanisms work through the relative unit cost and price. Moreover, the effect of a given cost difference is larger the higher the elasticity of substitution among products σ_i and the lower the scale elasticity μ_i in the i:th industry.

Assuming σ and μ to be constant across industries, and noting that all terms in (2.3.3) with index w, i.e. world averages, will appear as industry or country fixed effects (intercept dummies) we may write the corresponding regression equation

$$\ln r_{ij} = \sum_{i=1}^{n}\gamma_{1i}D_i + \sum_{j=1}^{M}\gamma_{2j}D_j + \gamma_3 \ln A_{hij} + \gamma_4 \ln q_{hij} +$$
$$+\sum_{k=1}^{m}\gamma_{5k}\alpha_{ik}\ln w_{jk} + \varepsilon_{ij} \qquad (2.3.4)$$

where we expect $\gamma_3 > 0$, $\gamma_4 > 0$ and $\gamma_{5k} < 0$ for all factors $k = 1...m$.

2.4 Sources of knowledge

2.4.1 The general framework

Superior technology or know-how available to firms in a certain industry in a particular country is introduced in the model in the previous section as a Hicks-neutral shift in the production function, represented in (2.1.1) by A_{hij}. But what are the causes of international differences in the A_{hij}:s? How does new knowledge develop and spread? How is international competitiveness affected?

New, economically relevant knowledge available to a firm may come from learning by doing, i.e. efficiency increases over time with experience of production, or it may require that resources are used for R&D within the firm. In addition, knowledge may spread from other firms, either through sales of licenses or in the form of spillover effects through imitation. Since technology is a non-rival good, and at least to some extent non-excludable, the innovator often cannot capture the full value of his invention, and new knowledge will be available to other users. However, utilization of knowledge spillovers is not costless. Studies show that costs of copying technology may be substantial (Cohen and Levinthal 1989, Mowery and Rosenberg 1989). Moreover, own research and skilled personnel may be a necessary condition for receiver capacity.

Technology spillovers may be local or global. There may be spillovers within as well as among industries. The absorption of global spillovers may be positively related to the degree of openness, measured by international trade as proportion of GDP (Coe and Helpman 1995). Finally, some technical progress may be achieved only through investment in new capital goods.

Let us write the level of technology in firm *h* in industry *i*, country *j*, A_{hij} in (2.1.1), as a function of the different sources of knowledge available. Knowledge may be acquired by learning (L_{hij}), produced from the firm's own R&D activity (s_{hij}), or obtained by various spillover mechanisms from research in other firms in the domestic industry (S_{ij}), other sectors in the home country (S_j) or the world market (S_i)[6]. In addition to these sources of disembodied technical change there may also be technical progress embodied in new capital goods (s^e_{hij}):

$$A_{hij} = F(L_{hij}, s_{hij}, S_{ij}, S_j, S_i, s^e_{hij}) \qquad (2.4.1a)$$

Learning by experience from production is usually thought of as proportional to the learning period or to cumulated production of the firm over time (Berndt 1991), thus creating dynamic economies of scale.[7] If learning is spread locally to all firms in the industry -- e.g. if all learning is

[6] Note that the impact on A_{hij} of global spillovers may depend on firms' own research as well as the degree of openness of the home economy.

[7] In a study of the semiconductor Irwin and Klenow (1994) discerned significant learning effects. Firms learn most from their own production but learning also spills over between firms in the same country as well as between firms in different countries.

embodied in the competence of workers that frequently change jobs -- it is the aggregate industry production cumulated over time, $\tilde{q}_{ij}$, that matters:

$$\tilde{q}_{ij} = \sum_{s=t-\tau}^{t} q_{ijs} \tag{2.4.1b}$$

2.4.2 R&D stock per firm or per unit of output?

Let us for the moment neglect spillovers and assume that knowledge generated by R&D is a private good which is totally firm specific and cannot be used elsewhere. Following the standard production function approach (Griliches 1995) we assume that total factor productivity of a firm is determined by the firm's available stock of knowledge (s_{hij}), obtained by cumulating the firm's R&D expenditure over a relevant period of time, and deducting for obsolecence.

In this study, however, we have no access to firm data; all data are industry totals. Thus we have to work with averages for the "representative" firm or product. A commonly used technology indicator (cf. OECD 1986, Griliches 1995) is the R&D intensity, i.e. R&D expenditure as a proportion of value added. We use here the cumulated R&D *stock* of the industry relative to industry value added:

$$s_{hij}^{q} = \frac{S_{ij}}{q_{ij}} \tag{2.4.2a}$$

This may be appropriate if we think of multi-product firms where R&D expenditure are fixed costs pertaining to individual products, and where output of each product is the same. The relevant concept will then be total industry R&D stock per unit of output in industry i in the j:th country.

In (2.4.2a), firm size does not matter. However, if the knowledge stock of the firm was equally applicable to all its products, or if we assume single-product firms, R&D expenditure will be a fixed cost at the firm level. If all firms in the i:th industry in country j were identical, each producing one single product, s_{hij} for the representative firm may be approximated by dividing the cumulated series of aggregated R&D expenditure, i.e. the stock of knowledge, for the i:th industry in the j:th country by the number of firms:

$$s_{hij}^{N} = \frac{S_{ij}}{N_{ij}} \tag{2.4.2b}$$

(2.4.2b) implies that if industry R&D stock and output are the same in two countries, the country with fewer and larger firms is expected to have a competitive advantage. Another way of introducing economies of scale in R&D at the firm level is to add an interaction term to (2.4.2a):

$$\gamma_{32} \ln s^q_{hij} + \gamma_{33} (\ln s^q_{hij} \ln q_{hij}) \qquad (2.4.2c)$$

The impact on efficiency of increasing industry R&D intensity will then depend on average firm size; we expect $\gamma_{33} > 0$. We will use (2.4.2a) and (b) as alternative variables in the empirical analysis.

2.4.3 Measuring R&D stocks

Stocks of knowledge by industry and country may be calculated from time series of R&D expenditure. Let us assume that technical progress is purely disembodied. Following Hall and Mairesse (1995) we use the formula

$$S_{ijt} = (1 - \delta_S) S_{ijt-1} + R_{ijt-1} \qquad (2.4.3a)$$

where S_{ijt} is the knowledge (R&D) capital stock in industry *i*, country *j*, at the beginning of period *t*, R_{ijt-1} is expenditure on R&D, industry *i*, country *j*, time *t-1* in constant prices and δ_S the rate of depreciation of knowledge, i.e. the rate at which knowledge becomes obsolete. A benchmark S_1 is obtained as

$$S_{ij1} = \frac{R_{ij1}}{g + \delta_S} \qquad (2.4.3b)$$

where *g* is the rate of growth of R&D in the pre-sample period, i.e. up to $t = 1$ (assumed constant over time).

Our first and simplest hypothesis is that competitiveness is determined by learning and the stock of knowledge in the representative firm or per unit of output in the industry:

$$A_{hij} = F(L_{ij}, s_{hij}) \qquad (2.4.4a)$$

Thus in the regression equation (2.3.4) we substitute the expression

$$\gamma_{31} \ln \tilde{q}_{ij} + \gamma_{32} \ln s_{hij} \qquad (2.4.4b)$$

for the technology term $\gamma_3 \ln A_{hij}$, where s_{hij} is measured alternatively by (2.4.2a) or (b), or $\gamma_{32} \ln s_{hij}$ is replaced by (2.4.2c). Additional hypotheses are tested by adding variables to this basic equation.

2.5 Technology spillovers

2.5.1 Knowledge as a local public good: local externalities from R&D

Let us now assume that there is no firm specific, excludable knowledge at all, and that the national stock of knowledge generated by R&D in the industry is shared freely by all domestic firms, i.e. that knowledge is a local public good. This means that there is a positive scale effect of the common R&D effort on the industry level. Then

$$s_{hij} = S_{ij} \qquad (2.5.1a)$$

This requires that there is no duplication of research effort, and that there is a complete national -- but no global -- spillover of knowledge within an industry.

A less extreme case would be obtained by assuming that the stock of knowledge of the firm, and thus its level of technology, may be influenced both by the R&D activity of the firm itself, producing firm specific (excludable) as well as some non-excludable knowledge, and by the total R&D effort of the industry in the j:th country, of which some proportion may be treated as a local common good (Grossman and Helpman 1991). Thus the impact on efficiency of a given level of R&D effort of the individual firm may depend on the level of common knowledge, which in turn will be proportional to cumulated R&D expenditure of the industry. We may test the hypothesis of complementarity of private and public knowledge by adding

$$\sum_{g=1}^{2} \gamma_{34g} G_g \ln s_{hij} \qquad (2.5.1b)$$

to the expression (2.4.4b), where the G_g:s are slope dummy variables indicating if the domestic R&D stock in the i:th industry is large, medium or small in an international comparison.

Another possibility is that the impact of firms' R&D on competitiveness may reflect differences in the size of the domestic, economy-wide knowledge base, which may be important for the output of the R&D of the firm. To test for this we define the G_g:s in (2.5.1b) as slope dummies for R&D abundant, medium and R&D scarce countries. The criterion used -- total R&D stock in the manufacturing industry -- introduces a scale effect on the economy level.

2.5.2 Global spillovers

There may also be international spillovers of new knowledge, i.e. that firms in a country may make use of knowledge developed by R&D in foreign firms. In the extreme case of perfect global spillovers, competitiveness and specialization would not be affected at all, since the resulting increase in productivity would be the same in all countries. However, countries may differ in their ability to absorb such spillovers. Following Coe and Helpman (1995), we add a variable OP_j, the trade ratio in country j -- exports plus imports of goods and services as a proportion of GDP -- to equation (2.4.4b) in order to test the hypothesis that the capacity to absorb a given stock of international common knowledge, and to use it to improve competitiveness, increases with the degree of openness.[8]

2.6 *Impact of R&D differing among industries*

It is possible that the relative R&D effort of the firm is more important for competitiveness in some sectors than in others. In particular, this might be true for firms competing in "new" product groups -- in the product cycle sense -- where products and processes are continuously changing, compared to more mature industries. Since the former industries should be more R&D intensive than the latter, this hypothesis may be tested by adding

$$\sum_{r=1}^{2} \gamma_{36r} R_r \ln s_{hij} \qquad (2.6.1)$$

where the R_r:s are slope dummy variables for high, medium and low R&D intensity industries,[9] to equation (2.4.4b).

[8] The degree of openness may affect a country's capacity to utilize global spillovers in various ways. First, trade is a mechanism through which technological knowledge is transmitted internationally. International trade increases the availability of differentiated intermediate products. New technology is embodied in imported capital goods. Second, international competition forces domestic producers to be informed about and use the internationally best known technology to stay competitive. However, in this study we cannot quantify the relative importance of these factors. Moreover, the trade ratio is an imperfect measure of the capacity to absorb new knowledge, since some technology flows may be unrelated to the exchange of goods and services.

[9] An explanation for this in terms of our model would be to allow elasticities of substitution and economies of scale to differ among industries (cf. equations 2.3.2a and

2.7 Embodied technical change

If the level of technology for a given vintage of capital does not change over time, and if machines of later vintages are more efficient than older ones, the average level of technology at a given point in time will depend not only on the knowledge frontier, i.e. the efficiency of the most recent vintages, but also on the age composition of the capital stock, which in turn depends on the time path of gross investment. We will assume here that such technical progress is potentially available globally to all producers, since it is embodied in internationally tradable machinery. Differences among producers with respect to average level of technology will then depend only on the rate of investment.

If the capital/output ratio θ_i in an industry is constant across countries we may write the investment ratio (i.e. investment to value added, neglecting the time index) as a linear function of the rate of growth of the capital stock, $\hat{K}_{ij}$, and the rate of depreciation δ_{Kij}:

$$\frac{I_{ij}}{q_{ij}} = \frac{dK_{ij} + \delta_{Kij} K_{ij}}{q_{ij}} = \frac{dK_{ij}}{K_{ij}} \frac{K_{ij}}{q_{ij}} + \delta_{Kij} \frac{K_{ij}}{q_{ij}} = \theta_i (\hat{K}_{ij} + \delta_{Kij}) \tag{2.7.1}$$

Thus a high investment ratio indicates either a high rate of growth of the capital stock or a high depreciation rate and thus a short life length of capital. In both cases this implies a low average age of the capital stock, i.e. a high proportion of the most recent vintages and thus a high average level of efficiency. To test this possibility we include the average investment ratio in firm h, industry i, country j, calculated as

$$s^e_{hij} = \frac{1}{\tau} \sum_{v=t-\tau}^{t} \frac{I_{ijv}}{q_{ijv}} \tag{2.7.2a}$$

This takes account of the differences in average level of investment ratio but not of the time profile of investment. This may be done by introducing capital depreciation:

$$s^e_{hij} = \sum_{v=t-\tau}^{t} \frac{I_{ijv}}{q_{ijv}} (1 - \delta_{Ki})^{t-v} \tag{2.7.2b}$$

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b), which could be introduced as industry specific slope variables. However, we have not explored the possibilities that the impact of other variables than R&D may also differ among industries.

3. Data and methods

According to equation (2.3.3) countries will specialize on industries intensively using their cheap resources. Our theoretical model is formulated in terms of cost shares of factors and national factor prices. We use factor prices except for natural resources -- arable and forest land -- where only quantities are available. However, some prices (e.g. relative wage for skilled labor) are available only for a limited number of countries. In order to expand the sample we have estimated a second set of equations where we replace prices with factor endowments. It can be shown that in a multi-sector economy in autarky, a country's abundant factors tend to be cheap, i.e. factor prices and endowments are negatively correlated.[10] As shown in *table 1*, factor prices and factor endowments in our sample are in fact negatively correlated.

Table 1 Correlations between factor prices and factor endowments

Factor of production	Correlation
Physical capital	–0.63 (0.02)
Human capital	–0.54 (0.10)
Electrical energy	–0.64 (0.03)

Parentheses ( ) give the significance level of correlation

Surveys of empirical work (e.g. Leamer and Levinsohn 1995 and Deardorff 1984) conclude that supplies of natural resources affect industrial localization, not only of extractive industries but also of processing industries. In addition, both human and physical capital have been found to be important. In principle, one should include resources which are internationally immobile,[11] where endowments and/or prices differ among countries, and requirements (cost shares) differ among industries. In this

[10] Formally, this is derived for identical and homothetic demand, perfect competition and identical technology (Ethier 1984, p. 176).

[11] By definition, arable and forest land are perfectly immobile; international trade in roundwood and electrical energy is very low relative to production. International mobility of skilled labor is still rather low, even within the European Single Market. Since financial capital as well as machinery both are highly mobile across countries it may be argued that capital should not be included in a country's (exogeneously given) factor endowments (cf. Wood 1994); we have, however, kept the capital variable.

study, we have included interaction variables measuring *national* prices or quantities, in combination with *industry* requirements, of

- forest land per worker/cost share of roundwood
- arable land per capita/food industry (a dummy)
- relative price of electrical energy or production of electrical energy per worker[12]/cost of electrical energy per employee
- return to capital/capital cost share of value added
- relative earnings of skilled labor or proportion of labor force with post-secondary education/wage costs accruing to workers with post-secondary education as share of value added.

According to our model, cost shares, α_{ki}, will be identical across countries. For some industry characteristics where national data are available we have calculated averages for the countries in the sample. For others - - especially human capital - - only Swedish data were available. A complete description of the data -- definitions and sources -- is given in the Appendix.

In (2.3.3) specialization is affected by relative firm size: the larger the firms, the lower will be costs and prices. We measure representative plant size, q_{hij} in (2.3.4), by the average number of employees per plant.[13]

To calculate knowledge capital stocks we use (2.4.3a) and (2.4.3b). We assume a depreciation rate of knowledge δ_S of 15 percent and a presample growth in R&D expenditure g of 6 percent (cf. Hall and Mairesse 1995). We also assume that investment in research add to the stock of productive knowledge capital with a lag of three years.[14] We have calculated knowledge capital stocks for 22 manufacturing industries in 13 OECD countries. *Table 2* reports average knowledge stocks as a share of value added (knowledge intensity) on industry level and classify industries into high, medium and low technology industries.

[12] A country's production of electrical energy may be treated as a "natural" resource to the extent that it is based on hydroelectric power. However, energy-intensive production, while historically based on cost advantages of abundant and cheap hydroelectric capacity, may over time acquire a technological advantage that creates the base for future competitiveness. This may lead to investment in "non-natural" energy production capacity such as nuclear power. Thus the causal interpretation of a correlation between energy production and the size of the energy-intensive industry sector may be ambiguous.

[13] Measuring size with output per plant or employees per plant is a matter of definition. The equations have been re-estimated with the former definition, giving basically the same results.

[14] According to a study by the U.S. Bureau of Labor Statistics (1989) the mean lag for basic research appears to be five years and two years for applied research.

Table 2 Knowledge capital stock in percent of value added by industry in 13 OECD countries 1990.

ISIC	Industry	Technology Level	Mean	Coefficient of variation
31	Food	Low	5.49	0.54
32	Textiles and clothing	Low	3.89	0.59
33	Wood and furniture	Low	1.97	0.71
34	Paper and printing	Low	3.03	0.88
351+352–3522	Chemicals	Medium	36.20	0.46
3522	Pharmaceutical	High	85.22	0.44
353+354	Refineries	Medium	22.49	1.05
355+356	Plastic and rubber	Medium	12.39	0.55
36	Stone, clay and glass	Low	8.89	0.62
371	Ferrous metals	Medium	13.09	0.61
372	Non-ferrous metals	Medium	16.22	0.75
381	Metal products	Low	6.68	0.58
382–3825	Other machinery	Medium	20.85	0.50
3825	Computers	High	81.88	0.69
383–3832	Electrical machinery	High	44.78	0.83
3832	Electronics	High	97.94	0.47
3841	Shipyards	Medium	12.85	0.75
3843	Motor vehicles	High	39.97	0.71
3845	Aircraft	High	117.42	0.74
3842+3844+3849	Other transport	Medium	28.04	1.17
385	Instruments	High	48.99	1.11
39	Other manufacturing	Low	7.24	0.56

Table 3 Knowledge capital stock in manufactures in 13 OECD countries 1990.

Country	Knowledge capital stock		
	Value (Billion USD PPP 1985 prices)		Share of value added (Percent)
Australia	3.47	Small	9.17
Canada	10.47	Medium	15.04
Denmark	1.97	Small	17.67
Finland	2.39	Small	16.24
France[1]	48.78	Large/Medium	28.34
Germany	85.11	Large	28.85
Italy	19.98	Medium	10.17
Japan	126.73	Large	22.60
The Netherlands	10.35	Medium	29.76
Norway	1.77	Small	25.27
Sweden	9.65	Medium	39.59
United Kingdom	50.38	Large	30.01
United States	420.79	Large	47.00

[1] France is not included in the regression analysis

Table 3 shows total knowledge capital in manufactures in each country both in absolute terms and as a share of value added. *Table 3* also divides the countries into groups with large, medium and small knowledge capital stock. It appears from *table 2* that there are significant variations in technology levels among manufacturing industries. The average knowledge intensity is only about 2 percent of value added in Wood & furniture, whereas it is more than 100 percent in Aircraft. Though small countries, such as Sweden and Norway, have the highest knowledge intensity in certain industries, it is evident from *table 3* that the bulk, in absolute terms, of OECD's knowledge stock in manufacturing -- almost 80 percent -- is concentrated to the US, Japan and Germany. The US also tops the ranking in relative terms, i.e. in percent of value added in manufactures.

4. Results

The econometric results in *table 4* supports the general hypothesis that firms' R&D efforts, by creating technology gaps, improve their competitive position. As shown in columns (i) and (v), average R&D stock per plant is positive and significant, even if complications such as scale economies or externalities in R&D, as well as differences in the importance of technology among industries, are neglected. Substituting the variable R&D stock per unit of output for R&D stock per plant (columns (iii) and (vii)) does not change this conclusion, [15] though the R&D effect appears to be slightly less significant. Our results thus are in line with numerous studies of the impact of R&D on productivity and growth (for a survey see Griliches 1995) as well as with earlier studies of R&D and competitiveness (Fagerberg 1997, Amable and Verspagen 1995).

However, R&D is not the only factor influencing competitiveness. First, factor prices affect specialization, thus confirming the predictions from our model. Columns (i) to (iii) in *table 4* show that countries where energy and capital are cheap tend to specialize on industries using these factors intensively. For skilled labor the coefficient has the right sign but is not significant. [16]

[15] This indicates that the measurement problems with the variable number of plants (cf. below), and thus the potential errors in measuring R&D stock per plant, may not be important enough to affect the main conclusions.

[16] One possible explanation is that the measure of skilled labor -- proportion of workers with post-secondary technical/scientific education -- is positively correlated with the R&D-variables (correlations 0.6 to 0.7). Moreover, the country variation in human

Table 4 Determinants of international specialization in 22 manufacturing industries and 12 OECD countries.

Variable	Factor prices 7 countries*				Factor endowments 12 countries**			
	(i) OLS	(ii) Robust	(iii) OLS	(iv) OLS	(v) OLS	(vi) Robust	(vii) OLS	(viii) OLS
$\ln s^{\lambda}_{hij}$	0.03	0.03	-	0.05	0.04	0.04		0.06
R&D/plant	(1.75)	(1.60)		(1.99)	(2.45)	(2.25)		(2.88)
	[2.29]			[2.22]	[2.46]			[3.04]
$\ln s^{q}_{hij}$	-	-	0.03	-	-	-	0.04	-
R&D/output			(1.59)				(2.31)	
			[2.11]				[2.38]	
$\ln \tilde{q}_{ij}$	0.21	0.21	0.22	0.21	0.21	0.20	0.22	0.24
Learning	(6.06)	(6.04)	(6.54)	(5.45)	(7.71)	(7.91)	(8.24)	(7.93)
	[5.95]		[6.39]	[4.60]	[7.05]		[7.66]	[6.72]
$\ln q_{hij}$	0.11	0.09	0.13	0.12	0.12	0.12	0.16	0.13
Plant size	(2.52)	(2.14)	(3.58)	(2.31)	(3.25)	(3.32)	(4.75)	(3.07)
	[3.36]		[4.60]	[2.91]	[2.73]		[4.02]	[2.78]
$\alpha_{Ki}\ln w_{Kj}$	−12.13	−13.01	−12.17	-	−6.32	−4.96	−6.49	-
Capital	(−3.38)	(−3.60)	(−3.38)		(−2.85)	(−2.36)	(−2.92)	
	[−4.30]		[−4.49]		[−2.70]		[−2.79]	
$\alpha_{Hi}\ln w_{Hj}$	−1.97	−1.89	−2.05	-	0.86	0.47	0.85	-
$\alpha_{Hi}\ln h_j$	(−1.29)	(−1.23)	(−1.34)		(1.73)	(1.00)	(1.70)	
Skilled labor	[−1.41]		[−1.45]		[1.64]		[1.60]	
$\alpha_{Ei}\ln w_{Ej}$	-1.6×10^{-6}	-1.6×10^{-6}	-1.6×10^{-6}	-	9.8×10^{-6}	8.9×10^{-6}	9.9×10^{-6}	-
$\alpha_{Ei}\ln e_j$	(−4.68)	(−4.83)	(−4.77)		(5.65)	(5.43)	(5.67)	
Energy	[−5.58]		[−5.67]		[6.31]		[6.41]	
$\alpha_{Ti}\ln t_j$	3.9×10^{-6}	3.8×10^{-6}	3.9×10^{-6}	-	2.8×10^{-6}	3.0×10^{-6}	2.8×10^{-6}	-
Forest land	(3.99)	(3.80)	(3.97)		(2.98)	(3.32)	(2.99)	
	[6.46]		[6.33]		[3.56]		[3.56]	
$\alpha_{Ai}\ln a_j$	0.05	0.01	0.05	-	0.09	0.07	0.09	-
Arable land	(0.75)	(0.23)	(0.73)		(1.74)	(1.58)	(1.77)	
	[0.95]		[0.95]		[3.30]		[3.43]	
Constant	−6.27	−6.14	−6.14	−6.70	−7.43	−6.54	−7.16	−6.97
F	16.39	9.08	16.60	6.81	16.20	16.59	16.01	9.86
Country effects	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/
F	13.19	6.64	13.32	11.16	13.63	9.38	13.66	11.89
Industry effects	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/	/0.00/
$\bar{R}^2$	0.74		0.74	0.59	0.66		0.66	0.56
F	12.52	12.19	12.44	7.92	12.76	12.62	12.71	9.82
Obs	144	144	144	144	247	247	247	247

capital endowments is rather limited in the sample, since OECD countries with the lowest educational standards are generally excluded because of missing data.

Parentheses ( ) give OLS t statistics, square brackets [ ] White's (1980) heteroskedasticity-consistent t statistics and slashes / / the significance level of the F-test. * The 7 countries are Canada, Germany, the Netherlands, Norway, Sweden, the United Kingdom and the United States. ** The 12 countries are Australia, Canada, Denmark, Finland, Germany, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom and the United States. † In specification (i)-(iv) we use national prices, i.e. $\alpha_{Hi} \ln w_{Hj}$ and $\alpha_{Ei} \ln w_{Ej}$, and in (v) - (vii) national endowments, i.e. $\alpha_{Hi} \ln h_j$ and $\alpha_{Ei} \ln e_j$, for skilled labor and energy.

In columns (v) to (vii) we have replaced national prices of skilled labor and electrical energy with the corresponding endowment quantities (cf. section 3 and Appendix), thereby extending the sample. The expected sign of the factor requirements/endowments interaction variables is positive. The coefficients for arable and forest land as well as for energy and capital[17] are strongly significant[18], whereas the coefficient for skilled labor becomes weakly significant, all with the "right" sign. Our results are thus broadly in line with the findings in most of the empirical literature explaining international specialization based on the Heckscher-Ohlin paradigm (for surveys see Deardorff 1984 and Leamer and Levinsohn 1995), namely that countries tend to specialize on industries intensively using their cheap and/or abundant factors of production.

The conclusion that factor prices/endowments should be included in a comprehensive model of international specialization is stressed by the results in columns (iv) and (viii), where these variables have been left out. The coefficient for the R&D variable increases, and the explanatory value of the regression falls by 10 to 15 percentage points. Thus the importance of R&D might be overstated if factor prices/endowments are not included in the analysis.

Second, fixed country and industry effects are strongly significant. Thus competitiveness depends in addition on a number of country and/or industry characteristics not captured by our variables. One source of such fixed effects are the existence of trade surpluses/deficits in manufacturing in some countries, as well as surpluses/deficits of the country group as a whole in some products. Moreover, according to our theoretical model in

[17] Note that the capital variable is still calculated using capital price, as in (i)-(iv), so the expected coefficient is negative.

[18] The difference between column (v) where arable land is strongly significant and column (i) where it is not is that in the latter Australia and Denmark had to be excluded because of missing data. The variables measuring arable and forest land as well as capital are the same in all regressions in table 4.

section 2 fixed country and industry effects should influence the result (cf. 2.3.3).

Third, there is evidence for the existence of (static) economies of scale on the plant level in production, as well as of dynamic scale effects (on the industry level) from learning. However, since these variables -- firm size and cumulated production -- are likely to be less reliable measures of the corresponding theoretical concepts than other data,[19] one should not overstress these findings. We have re-estimated all equations without these two variables; this increases the significance of the other variables in general, and of R&D in particular, but does not upset the conclusions.

Tests indicate that heteroskedasticity is likely to be present in most of the equations; thus we report *t* statistics estimated both by OLS and by White's heteroskedasticity consistent method. These *t* values differ somewhat, but the main conclusions remain. Nor are the results strongly dependent on a limited number of observations with extreme values of the variables. In most cases, robust regressions in columns (ii) and (vi), where such observations are given lower weight, do not change the coefficients nor the *t* values very much. The estimated R&D coefficients for the R&D impact remain virtually unchanged. This holds also for the results in *table 5*, where the robust regression results are not shown.

Having estimated the "basic" equations in *table 4*, we examine a number of additional hypotheses discussed in section 2 by adding new variables. In *table 5* we report only the coefficients for those variables that have been *added* to the basic equations (v) and (vii) in *table 4* in order to test additional hypotheses.[20] Since the relevant variables are strongly correlated we do not include them all together in the same regression.[21]

[19] National data on number of plants do not use the same definitions. While e.g. Canada surveys all plants, Sweden includes only plants with more than five employees and Germany plants belonging to firms with more than 20 workers. This introduces measurement errors in the variables plant size (workers per plant) and R&D stock per representative firm (industry R&D stock divided by the number of firms).

[20] Since the choice between factor prices or factor quantities does not seem to matter much for the basic results, we have used the latter version, in order to increase the sample size (cf. above).

[21] We do not test simultaneously for industry and country slope dummies, interaction effects, etc. In other words we do not test for, e.g. the presence of externalities, taking account of economies of scale and varying R&D impact. Since we do not discriminate between alternative "models" as expressed in regression equations containing different R&D variables, we present no single "preferred equation".

Table 5 Testing additional R&D hypotheses. Estimates of the partial effect of specialization of additional technology variables.

Row	Hypothesis/variable	s^N_{hij}	$\bar{R}^2$	s^q_{hij}	$\bar{R}^2$
1	Scale economies in R&D	-	-	0.036	0.669
	$\ln s^q_{hij} \ln q_{hij}$			(3.02)	
				[2.75]	
2	Domestic R&D spillovers within industries				
	$\ln s_{hij}$ (S_{ij} large)	0.046	0.656	0.087	0.662
		(2.46)		(3.32)	
		[2.50]		[3.70]	
	$\ln s_{hij}$ (S_{ij} medium)	0.042		0.052	
		(2.16)		(2.45)	
		[2.17]		[2.70]	
	$\ln s_{hij}$ (S_{ij} small)	0.045		0.037	
		(2.16)		(1.96)	
		[2.19]		[1.98]	
	International R&D spillovers				
	$\ln OP_j$	0.009		0.008	
		(5.08)		(4.61)	
		[5.62]		[4.87]	
3	Domestic R&D spillovers				
	$\ln s_{hij}$ (S_j large)	0.065	0.659	0.093	0.666
		(3.02)		(3.63)	
		[3.27]		[4.26]	
	$\ln s_{hij}$ (S_j medium)	0.037		0.032	
		(1.84)		(1.41)	
		[1.93]		[1.62]	
	$\ln s_{hij}$ (S_j small)	0.039		0.021	
		(1.68)		(0.86)	
		[1.49]		[0.74]	
	International R&D spillovers				
	$\ln OP_j$	0.011		0.006	
		(4.10)		(3.32)	
		[5.36]		[3.32]	

Table 5 (continued).

Row	Hypothesis/variable	s_{hij}^{N}	$\overline{R}^2$	s_{hij}^{q}	$\overline{R}^2$
4	Industry specific R&D impact				
	$\ln s_{hij}$ high	0.059 (2.64) [2.54]	0.662	0.047 (1.79) [1.67]	0.652
	$\ln s_{hij}$ medium	0.049 (2.14) [2.14]		0.044 (1.54) [1.54]	
	$\ln s_{hij}$ low	–0.012 (–0.40) [–0.45]		0.031 (0.89) [1.16]	
5a	Embodied and disembodied knowledge				
	$\ln s_{hij}^{e}$ (2.7.2a)	0.171 (3.58) [4.17]	0.674	0.162 (3.36) [3.90]	0.672
	$\ln s_{hij}$	0.037 (2.01) [2.23]		0.031 (1.64) [1.90]	
5b	$\ln s_{hij}^{e}$ (2.7.2b)	0.155 (3.34) [3.78]	0.671	0.146 (3.11) [3.50]	0.669
	$\ln s_{hij}$	0.039 (2.12) [2.39]		0.033 (1.78) [2.09]	

Parentheses ( ) give OLS t statistics and square brackets [ ] White's (1980) heteroskedasticity-consistent t statistics. The number of observations is 247 except in row 5a and 5b where it is 233.

All other variables, i.e. country and industry dummies, factor endowments and measures of scale and learning effects, are included as in columns (v) and (vii) in *table 4* but not reported; the results for these variables do not differ much from those reported in *table 4*.

The first row tests for the existence of economies of scale in R&D on the firm/plant level (as distinct from general effects of firm or plant size) by including an interaction variable combining the effect of industry R&D intensity (R&D stock relative to value added) with average plant size (expression 2.4.2c). The coefficient for this variable is positive and significant,[22] thus supporting the hypothesis that the impact of a given R&D stock per unit of output may be higher for countries with large firms. Our interpretation is that this highlights the role of R&D as a fixed cost at the firm level.

Mansfield et al. (1977), Scherer (1982) and others have shown that social returns on R&D strongly exceeded private returns, which implies that spillovers may be important for productivity growth. Such spillovers may be local or global. The second row in *table 5* supports the idea of domestic within-industry spillovers. The impact of firms' own research on competitiveness seems to increase with the size of the total domestic knowledge stock in the industry.[23] This holds when s_{hij} is defined as R&D stock relative to value added, but not for R&D per plant.

The absolute importance of global spillovers cannot be estimated in this paper.[24] However, the results in rows 2 and 3 of *table 5* indicate that - - given the amount of globally available common knowledge - - a country's capacity to absorb such knowledge and to use it to improve its competitiveness may increase with the degree of openness, thus confirming the results of Coe and Helpman (1995).

Local spillovers may be economy-wide rather than within-industry. Row 3 in *table 5* shows the results of a regression where the R&D slope dummy is based on the size of the total national R&D stock in manufacturing, rather than the stock in each industry. The results are basically the same: the impact of a given R&D stock per plant, as well as of a given R&D intensity in the industry, seems to be larger in countries with a large common stock of locally available knowledge. This is in line with the findings of Bernstein and Nadiri (1989) that local spillover effects on productivity may extend over industry boundaries. In fact, data give a slightly stronger support for the the economy-wide rather than the intra-industry effects. However, the results also indicate that this implicit handicap for small countries may be mitigated by openness.

Row 4 in *table 5* indicates that the impact of technology on competitiveness differs among high-tech, medium and low-tech

[22] Note that the variables R&D stock per firm and firm size remain in the equation.

[23] Assuming spillovers to follow input flows, Fagerberg (1997) found national spillovers to be more important than global.

[24] Since commonly shared spillovers do not affect competitiveness.

industries.[25] The coefficient for R&D stock per firm is positive and significant for high and medium technology industries, but very low and insignificant for the low-technology sector, where competitiveness more may be a matter of factors such as wage costs. Still, the group for which "technology matters" covers more than the "traditional high-tech" group.

The last two rows of *table 5* support the hypothesis that technical progress influencing competitiveness may be both disembodied and embodied in new capital goods. The first component depends (disregarding spillovers) only on average R&D stock per plant or per unit of output. If the "frontier" technology is embodied in new machinery which is internationally freely traded, the average efficiency of a producer's capital stock relative to competitors depends only on the investment ratio in the previous period (and possibly also on the time path of investment during that period). *Table 5* shows both components of technical progress -- disembodied and embodied -- to have positive and significant effects on competitiveness.

5. Limitations of the analysis

In our model, R&D activity is exogenously given. Thus we neglect a basic issue in modern growth theory, namely intentional (endogeneous) innovation in response to profit opportunities (Grossman and Helpman 1991). It is therefore important to be careful when making causal interpretations of the results. A related econometric point is the issue of simultaneity bias, i.e. if competitiveness also affects R&D. Unfortunately, good instruments are lacking. However, since competitiveness in 1990 in the model depends on cumulated R&D expenditure during a previous 15 year period, simultaneity should not present a serious problem.

Moreover, factor endowments are also assumed to be given. In a more realistic model, endowments of e.g. capital -- both human and physical -- are the results of investment decisions determined by expected rates of return. Since these accumulation processes may be interrelated (if e.g. some factors are strongly complementary), caution in causal interpretation is again required.

In section 2 we attempt to model the impact of what is basically process innovations via costs on competitiveness. The model does not explicitly

[25] The classification is based on average R&D stock in per cent of value added as shown in *table 2*.

treat product innovations. Nevertheless, it seems obvious that new and improved products, by shifting consumer demand among firms, increases competitiveness and therefore should be captured by the R&D variables in the empirical analysis.

Our analysis of e.g. economies of scale in R&D is limited by the lack of firm data on R&D and sales; we can only work with industry averages. Moreover, we do not explicitly take account of differences among industries in elasticities of substitution among products or the extent of economies of scale. Finally we avoid the complications involved in modelling the dynamic interactions between R&D activity, operating technology and market shares that becomes necessary in a pooled time series cross-section analysis using annual data.

6. Conclusions: a choice among paradigms?

The results in this paper show that technology has a significant effect on international competitiveness. But so have factor prices and endowments. Our conclusion is thus that in order to explain countries' comparative advantages and patterns of international specialization it is necessary to combine elements from both competing paradigms -- the factor endowments or Heckscher-Ohlin and the technology or Ricardian -- rather than to substitute one for the other.

Firms' R&D activity is important for international competitiveness. However, the process of acquiring a technological advantage seems to be rather complicated, and involve other factors than the firm's own R&D intensity. Our results indicate that R&D may be treated as a fixed cost, and thus that there are economies of scale in research on the firm (plant) level. In addition there seems to be scale effects on the domestic industry as well as on the national level, which are caused by local externalities/spillovers. This means that size matters on all levels. To some extent, this size handicap for small countries might be mitigated by openness to trade. It appears that R&D as a factor shaping competitiveness is really crucial mainly for high and medium technology sectors. Finally, technological progress seems to be both embodied and disembodied, which means that acquiring technical leadership requires not only intensive research activity but also a high rate of investment.

Appendix Variables: definitions, measurement and sources

Coefficient of specialization:

$$r_{ij} = \frac{Q_{ij}}{C_{ij}} = \frac{Q_{ij}}{Q_{ij} + X_{iwj} - X_{ijw}}$$

Q_{ij} production (gross output), industry i, country j, average 1989-91.

C_{ij} consumption, industry i, country j, average 1989-91.

X_{iwj} import, industry i, from the whole world w to country j, average 1989-91.

X_{ijw} export, industry i, from country j to the whole world w, average 1989-91. Source: OECD (1994b).

Knowledge capital stock:[26]

$$S_{ijt} = (1 - \delta_S) S_{ijt-1} + R_{ijt-1}$$

S_{ij} knowledge capital (R&D) stock, industry i, country j, 1990, US dollar 1985 PPP, 1985 prices.

R_{ijt} expenditure on R&D, industry i, country j, 1973-87, US dollar 1985 PPP, 1985 prices. R&D expenditures R_{ijt} are deflated by the manufacturing sector value added deflator. Source: OECD (1996a) and OECD (1994b).

δ_S depreciation rate of knowledge.

Firm specific knowledge stock: $s_{hij}^{N} = S_{ij} / N_{ij}$ or $s_{hij}^{q} = S_{ij} / q_{ij}$

N_{ij} number of establishments, industry i, country j, 1990. Source: OECD (1995b).

q_{ij} value added, industry i, country j, 1990, US dollar 1985 PPP, 1985 prices. Source: OECD (1994b).

[26] Three observations were deleted because calculated R&D expenditure as a share of value added were extremely high (close to or larger than one), namely Australia (ISIC 3832), Denmark (ISIC 39), and the Netherlands (ISIC 383–3832).

Embodied technology:[27]

$$s_{hij}^{e}=\frac{1}{\tau}\sum_{v=t-\tau}^{t}\frac{I_{ijv}}{q_{ijv}^{*}} \text{ or } s_{hij}^{e}=\sum_{v=t-\tau}^{t}\left(1-\delta_{i}^{K}\right)^{t-v}\frac{I_{ijv}}{q_{ijv}^{*}}$$

δ_{Ki} rate of depreciation of physical capital, industry i. Source: Hansson (1991).

I_{ijv} gross fixed capital formation, current prices, industry i, country j, 1976-90. Source: OECD (1994b)

q_{ijv}^{*} value added, current prices, industry i, country j, 1976-90. Source: OECD (1994b)

τ 15 years

Plant size: $q_{hij}=L_{ij}/N_{ij}$

L_{ij} number of employees, industry i, country j, 1990. Source: OECD (1994b).

Cumulated production: $\tilde{q}_{ij}=\sum_{s=t-\tau}^{t}q_{ijs}$

q_{ijs} value added, industry i, country j, 1970-89, US dollar 1985 PPP, 1985 prices. Source: OECD (1994b).

Physical capital: $\alpha_{Ki}\ln w_{Kj}$

α_{Ki} share of operating surplus in value added , industry i, average for all countries j in the period 1980-90. Source: OECD (1994b).

w_{Kj} return to physical capital calculated as average operating surplus in manufacturing 1980-90 relative to the manufacturing capital stock 1985.

$$w_{kj}=\frac{\sum_{t=1980}^{1990}(Y_{jt}-W_{jt})/11}{K_{j85}}$$

Y_{jt} value added in manufacturing, country j, 1985 prices. Source: OECD (1994b).

W_{jt} labor compensation in manufacturing, country j, 1985 prices. Source: OECD (1994b).

[27] The extreme value of refineries (ISIC 353+354) in Norway has been excluded.

K_{j85} capital stock in manufacturing, country j, 1985 prices. Source: OECD (1993).

Skilled labor: $\alpha_{Hi} \ln w_{Hj}$ and $\alpha_{Hi} \ln h_j$

$$\alpha_{Hi} = \sum_{j=1}^{12} \left(\alpha_{Lij} \left(W_i^S / W_i \right) \right) / 12$$

α_{Hi} share of skilled labor compensation in value added , industry i, average for 12 countries in the period 1980-90.

α_{Lij} share of wages in value added, industry i, country j, average 1980-90. Source: OECD (1994b).

W_i^s compensation to employees with post-secondary education, industry i, Sweden, 1990. Source: SCB Regional Labor Statistics.

W_i total labor compensation, industry i, Sweden, 1990. Source: SCB Regional Labor Statistics.

w_{Hj} relative wage of skilled labor: ratio of mean annual earnings by educational qualifications (level B/ level E), country j, middle of the 1980s. Source: OECD (1996b)

h_j number of graduates in science and engineering per 100,000 of population aged 25-35, country j, 1991. Source: OECD (1994a).

Energy: $\alpha_{Ei} \ln w_{Ej}$ and $\alpha_{Ei} \ln e_j$

α_{Ei} cost of electrical energy SEK per employee, industry i, Sweden, 1989. Source: SOS Manufacturing 1989.

w_{Ej} relative price of electrical energy, country j. Price of electrical energy for industrial users. Source: National Utility Services. Labor costs per hour in manufacturing. Source: Swedish Employers Federation (SAF).

e_j production of electrical energy kWh per worker, country j, 1990. Source: SCB (1993) and OECD (1995a).

Forest land: $\alpha_{Ti} \ln t_j$

α_{Ti} input of roundwood SEK per 10 000 SEK output, industry i, Sweden, 1985. Source: SCB (1992).

t_j hectare forest land per worker, country j, 1990. Source: SCB (1993) and OECD (1995a).

Arable land: $\alpha_{Ai} \ln a_j$

α_{Ai}	dummy variable for industry 31 (food)
a_j	hectare arable land per worker, country *j*, 1990. Source: SCB (1993) and OECD (1995a).

Openness:

$$OP_j = \left(\frac{X+M}{Y}\right)_j \quad \text{(average 1980-89)}$$

X_j	export of goods and services from country *j*
M_j	import of goods and services to country *j*
Y_j	GDP in country *j*. Source: OECD (1995c)

Factor prices, country coverage:
Data were available for return to capital for all 13 countries in table 3, for relative earnings of skilled labor for all except Finland, and for energy prices for all except Australia, Denmark and Japan.

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The Dynamics of European Industrial Structure

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Abstract

Why do countries' specialisation patterns change? Have these patterns become reinforced? In this paper, we use a trade model that incorporates endowments, technology, and increasing returns to scale (IRS) to address these questions. We study determinants of *changes* in specialisation among 10 European countries and 22 industries spanning the period 1976-96. There is no evidence of an increased concentration of increasing returns to scale industries in countries with large markets. Countries with high rates of capital accumulation have become increasingly specialised in capital-intensive industries; this holds for both human and physical capital. We find an increased specialisation of capital-intensive industries in capital-abundant countries. For human capital, on the other hand, there is a tendency towards convergence, i.e., countries with a low supply of skilled labour are catching up with human capital abundant countries. Results point at scale economies in R&D at the firm level, and that firm level R&D is what matters for increased competitiveness. Finally, there is robust evidence for interdependency in changes in specialisation patterns between domestic industries.

Keywords: competitiveness; productivity; trade; technology; technology transfers; R&D
JEL codes: C29 F12 O33 O52

* **Acknowledgements:** Financial support from Jakob Wallenbergs Forskningsstiftelse is gratefully acknowledged.

1. Introduction

Why do countries' specialisation patterns change and do countries factor abundances converge or diverge? In explaining trade patterns, two main explanations have dominated the literature for some time: the Hecksher-Ohlin approach, focusing on differences in endowments; and the Ricardian model, focusing on technological differences.

Few papers have analysed changes in countries' specialisation patterns. Exceptions are Proudman & Redding (2000) who utilise a transition matrix to analyse changes in the distribution of the G-5 countries' specialisation, and Redding (1999) who studies the dynamics of international specialisation among seven OECD countries and 20 industries.

In this paper, we build and estimate a modified version of the trade model utilised in Gustavsson *et al* (1997, 1999). Focus is on *changes* in countries' specialisation patterns and the model incorporates *endowments*, *technology,* and *increasing returns to scale.*

One feature that distinguishes this model from the vast majority of trade models, is that technological progress is endogenous by way of embedding a modified version of the Aghion & Howitt (1992) R&D driven endogenous growth model in the trade model.

We allow domestic industries to be interdependent through (1) inter industry technology transfers, (2) domestic, inter-industry demand linkages, and (3) via a general interdependence in the error term[1].

The ongoing European integration process can be seen as lowering costs involved in international transactions[2]. If there were no changes in endowments or technology, the integration process alone would reinforce countries' specialisation patterns according to their comparative advantages[3]. In such an environment, initial position is an important determinant of future changes in trade patterns. Initial levels may also be an important element determining future changes in trade patterns if countries' convergence towards the optimal production structure is sluggish. We use changes as well as initial levels when analysing changes in countries' specialisation. This simple trick may give us interesting information about the forces behind changes in countries' specialisation patterns.

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[1] Fagerberg (1997) and Coe & Helpman (1995) use I-O links when modelling technology spillovers transmitted via trade.

[2] Transaction costs might be seen as covering transportation and information costs as well as tariffs, NTBs, etc.

[3] In a Ricardian framework, this is easy to show since it reduces the range of non-traded goods. For this to hold in higher dimensions in a Heckscher-Ohlin framework see Ethier (1984) for details.

Empirical tests of the factor proportion model, beginning with Leontief (1954) have generally given weak support for the model. Several extensions of the model have been made in order to relax some of the underlying assumptions and increase its empirical performance. Contributions have been made by Maskus (1985) and Bowen (1987) for example. Baldwin (1971) makes an early, cross-commodity regression when he analyses how industries' export performance is related to various industry characteristics. Petri (1991) sets up a model that relaxes the factor price equalisation assumption when he analyses import and export penetration in 49 manufacturing industries in Japan[4].

Harrigan (1999) (and others) has found cross-country productivity differences to be substantial. Focusing on technology differences in explaining trade patterns, Balassa (1963) finds a positive correlation between export ratios and US/UK labour productivity while Mc Gilvray & Simpson (1973) find weak or no evidence for relative labour productivity to predict trade flows between the UK and Ireland. In the neo-Ricardian literature, or 'technology gap' models, Posner (1961) argues that innovations and technology gaps induce shifts in trade patterns, at least for the time it takes competitors to mimic the new technology. Fagerberg (1988) and Dosi, Pavitt & Soete (1990) analyse the impact of innovations on trade patterns. The latter find evidence for innovative activity to affect export patterns and the former a stronger relationship between technological variables and export compared to the impact of labour productivity on export.

Drawing on differences in technology and endowments, Trefler (1993, 1995) augments the factor proportion model in that he allows for *productivity differences* and home consumption bias in consumption. Harrigan (1997) and Gustavsson *et al* (1997) specify a model where endowments and technology jointly determine specialisation and trade patterns. Both find relative factor abundance and technology to be important determinants of trade patterns. One drawback of these models is that technology is exogenous and no geographical effects are included when explaining trade patterns. In Gustavsson (1999) we went one step further by making technology a function of R&D while the R&D process was theoretically unexplained.

The link between R&D, productivity, and trade, is a field where there are numerous empirical studies. Keller has, in a series of articles (see for example, Keller 1997, 2000), studied these links. He finds a positive impact of industries' R&D on productivity as well as substantial inter-industry and inter-country technology transfers where trade, to some extent, is a carrier of technology transfers. In analysing technology transfers, Brown & Conrad (1967) use an input-output (I-O) matrix to measure closeness of industries while Terleckyj

[4] For a survey of the empirical evidence, see Leamer and Levinsohn (1995).

(1974) use the capital and intermediate input matrix to proxy the distance between industries[5].

During the last decade, economists have rediscovered geography as a determinant for specialisation. Marshall (1920) argued that the decision of location of industrial activities is affected by three categories of returns to agglomeration. Briefly, he argued for: (1) spillovers that loosely speaking is in the air, (2) labour market pooling, and (3) forward and backward linkages. Krugman (1991) and Venables (1996) have formalised the forward and backward linkages, which in combination with increasing returns to scale and transportation costs, give rise to agglomeration. This strand of models has become labelled *the new economic geography literature*[6]. The new economic geography has inspired a set of empirical papers to incorporate agglomeration effects when analysing specialisation. Davis & Weinstein (1996, 1999) apply a model that nests an H-O model with an increasing returns model with "home market" effects. In the former paper, they study 22 OECD countries and find scant evidence for geography effects while the latter study on Japanese regions finds significant geography effects. Haaland *et al* (1999) examine sources of relative and absolute concentration of manufacturing activity. Amiti (1999) gives a brief survey of empirical evidence of agglomeration and examines changes in the Gini coefficient for a sample of European countries and industries. She finds (in line with Brulhart & Torstensson (1996)) increased concentration in high increasing return to scale industries, while the evidence is mixed for other industries.

We study ten European countries (nine of them are today members of the EU) and 22 industries spanning the period 1976-96.

The econometric analysis reveals that *cumulating productive factors* turn countries towards an increased specialisation in industries intensive in the factors they accumulate relatively much of. There is evidence of an increased concentration of capital-intensive industries in initially capital abundant countries. Those capital abundant countries also exhibit the highest capital accumulation ratios. We find the opposite to be true for human capital in that there is a tendency for a catching-up or convergence in human capital abundance among the countries in the sample.

The results point at scale economies in R&D at the firm level and that R&D at the firm level is what matters for increased competitiveness. We do not find any impact of industries' or countries' total R&D stocks on the growth in the coefficient of specialisation.

Analysing domestic industrial interdependency using I-O matrices, we find quantitatively small but significant inter-industry technology transfers. Inter-industry demand links are found to be of second order while there is robust

[5] See Stoneman (1995) and Griliches (1992) for a survey and findings on R&D and technology relationships.

[6] For models and a survey see Krugman, Fujita & Venables (1999) and Hanson (2000).

evidence for substantial interdependence in the error term. This means that if one industry increases its market share more than expected, we expect its close trading partners to move in the same direction; that is, a clustering behaviour of industries 'close' to each other.

The paper is organised as follows: section 2 presents the theoretical model; in section 3, the regression variables are presented; section 4 contains the econometric results; and section 5 concludes.

2.The model

2.1. Factor prices, goods prices and technology

The model used here is an extension of the one presented in Gustavsson *et al* (1997, 1999). Assume N traded goods $n = 1,...,N$ and J countries $j = 1,...J$. Each firm $f_{nj} = 1,...,F_{nj}$ produces a differentiated good using V factors of production $v = 1,...V$. Factors are mobile between industries but immobile between countries except human capital, which is assumed to be country- and industry-specific[7]. We do not assume factor price equalisation across countries. Each final good firm sells a differentiated good under monopolistic competition with free entry. On the factor market, we assume perfect competition. Assuming a generalised Cobb-Douglas technology, the production function for firm f in country j and industry n may be written as

$$y_{fnjt} = A_{fnjt} \prod_{v=1}^{V} v_{fnjt}^{\alpha_{vn}} \tag{1}$$

where returns to scale is given by

$$\sum_{v=1}^{V} \alpha_{vn} \equiv \mu_n . \tag{2}$$

Technology in one industry is assumed to be the same across firms in a certain country and differs across countries only with respect to productivity A_{fnjt}. For a given industry, elasticity parameters are assumed to be constant over time and identical across countries. Following Berndt (1991), cost minimisation yields the following expression for the log of unit cost[8].

$$\ln c_{fnjt} = \phi_n + \frac{1-\mu_n}{\mu_n} \ln y_{fnjt} - \mu_n^{-1} \ln A_{fnjt} + \sum_{v=1}^{V} \frac{\alpha_{vn}}{\mu_n} \ln w_{vjt} . \tag{3}$$

[7] In the empirical framework, human capital is treated as country-specific.
[8] See also, Gustavsson *et al* (1999).

c is unit cost, y_{fnjt} is firm size, A_{fnjt} is an index of technology, and w_{vjt} is the price of factor v in country j. If all firms in an industry in a country are identical, firms' unit cost is the same as the industrys' unit cost. The cost is decreasing in technology, increasing in factor prices and, given increasing returns to scale, decreasing in firm size. Monopolistic competition in the final good sector ensures that price equals unit cost.

2.1.1. Demand

Consumers' utility and demand is assumed to be of the (S-D-S)[9] form and identical for all consumers across countries. Products are differentiated among firms, and all firms in an industry in a country charge the same price. The utility of the representative consumer is given by

$$U = \prod_{n=1}^{N} \left(\sum_{j=1}^{J} F_{nj} D_{fnj}^{b_n} \right)_t^{\frac{\theta_n}{b_n}} \; ; \sum \theta_n = 1. \tag{4}$$

where D_{fnj} is demand from firm f in the nth industry in country j, F_{nj} is the number of firms in industry n in country j, and θ_n is the budget share allocated to products from industry n. This gives the following total demand of products from country j and industry n[10].

$$D_{nwjt} = \frac{F_{njt} p_{njt}^{-\sigma_n} \theta_n E_{wt}}{P_{nt}^{1-\sigma_n}} \; ; P_{nt} \equiv \left(\sum_{j=1}^{J} F_{njt} p_{njt}^{1-\sigma_n} \right)^{1/1-\sigma} . \tag{5}$$

E is expenditures, w is shorthand for the world, $\sigma_n = 1/(1-b_n) > 1$ is the elasticity of substitution among products in the nth industry, F_{njt} is the number of firms in industry n and country j at time t, and P_{nt} is the CES price index.

2.2. The coefficient of specialisation

Consider country j's trade with the rest of the world. One measure of relative competitiveness, specialisation, and net export, is the coefficient of specialisation defined as the ratio of gross value of production to consumption.

$$r_{njt} \equiv \frac{Q_{njt}}{C_{njt}} = \frac{C_{njt} + X_{njwt} - M_{nwjt}}{C_{njt}}. \tag{6}$$

Q is gross value of production, and X_{njwt} and M_{nwjt} are export and import in the nth industry in country j respectively; we note that $C_{njt} = \theta_n y_{jt}$. Using demand, as

[9] Spence (1976), and Dixit-Stiglitz (1977).

[10] See Helpman & Krugman, 1985, p 206.

specified in Eq. (5), and the definition of the coefficient of specialisation as stated in Eq. (6), we get the following expression for the log of the coefficient of specialisation:

$$\ln r_{njt} = (1-\sigma_n)\ln p_{njt} - (1-\sigma_n)\ln P_{nt} + \ln F_{njt} + \ln \frac{E_{wt}}{E_{jt}}. \qquad (7)$$

By monopolistic competition, unit cost equals price and we insert the expression for the log of unit cost in Eq. (3) into Eq. (7) and get the following expression for the growth rate in the coefficient of specialisation.

$$\begin{aligned} \Delta_t \ln r_{njt} &= -(1-\sigma_n)\Delta_t \ln P_{nt} + \Delta_t \ln \frac{E_{wt}}{E_{jt}} + \Delta_t \ln F_{njt} \\ &+ (1-\sigma_n)\frac{1-\mu_n}{\mu_n}\Delta_t \ln y_{fnjt} - (1-\sigma_n)\mu_n^{-1}\Delta_t \ln A_{fnjt} \\ &+ (1-\sigma_n)\sum_{v=1}^{V}\frac{\alpha_{vn}}{\mu_n}\Delta_t \ln w_{vjt}. \end{aligned} \qquad (8)$$

Market shares are increasing in technology, inversely related to national factor prices and, given IRS, increasing in firm size[11].

2.3. Endogenous technology

In the expression for the coefficient of specialisation, the state of technology is exogenous. In what follows we make R&D activity endogenous by using the model of creative destruction (Aghion & Howitt, 1992), where some extensions are made to adjust the model to a disaggregated set-up. Since we build on a well known model, the description is kept brief. In the first round, we apply the original model more or less intact. Industries are treated as independent of each other; hence innovations in one industry do not affect productivity in other industries. In the second round, the final good from an industry is used as an input in other domestic final good industries. By this manipulation, the impact of an innovation in an industry will be transferred across industries. We focus on the steady state (SS) solution. Calculations and steady state properties are given in Appendix 1.

[11] The right hand side variables on the first row correspond to changes in (1), the CES price index, P_{nt} (unobserved), (2), relative country size, (E_w/E_j) (almost time invariant), and (3), the number of firms, F_{njt} (we do not have time series data on the size and number of firms). In the econometric analysis, these variables will be suppressed into dummy variables.

2.3.1. Structure of the R&D model[12]

Within each industry there are three sectors: the *R&D Sector* (R&D), the *Intermediate good sector* (IG), and the *final good sector* (F).

The R&D Sector (R&D) uses industry-specific human capital as the only input in the production of new designs whose state of technology or 'generation' is indexed by (i). The industry-specific human capital H_n, is divided between R&D, denoted with subscript 2, H_{nj2}, and IG production indexed with 1, H_{nj1}, $H_{nj} = H_{nj1} + H_{nj2}$. In equilibrium, the price of a design will be such that the expected current value of IG firms' profit equals the price of the design. The number of R&D firms is indeterminate.

When an R&D firm creates a new design it sells it to the (potential) IG firms where only the firm that buys the design will be active and the old intermediate good will become obsolete; hence we assume innovations to be drastic. The active intermediate good firm has a perpetual monopoly in the production of the intermediate good and sells the intermediate good V_{xnj}, to the final good sector in the industry and country that the intermediate firm belongs to. The intermediate firm's production function is linear, $V_{xnj} = H_{nj1}$.

The *Final good sector* (F), is described above.

An innovation in industry n increases productivity in the final good sector by a factor of $\gamma^{\alpha_{nx}} > 1$, where γ measures the height of innovations and α_{nx} is the input coefficient of intermediates in final good production in industry n; hence $A(i+1)_{nj} = A(i)_{nj}\gamma^{\alpha_{nx}}$. The momentary probability for an innovation to occur is $\lambda H_{nj2}dt$. The steady state growth rate of total factor productivity (TFP) in an industry and country ($\mathrm{AGR_{nj}}$), is

$$\mathrm{AGR_{nj}} = \ln(\gamma^{\alpha_{xn}})\lambda H^{ss}_{nj2}. \tag{9}$$

From Eq. (9) we can see that, given that all final good firms in an industry and country share the same intermediate goods, the industry's productivity growth rate increases linearly with the *absolute* number of domestic R&D workers in an industry.

We can also imagine the case of firm-specific R&D, resulting in firm-specific designs and intermediates. In this case, it is the absolute number of R&D workers in the representative *firm*, $\overline{H}^{ss}_{\bullet nj2} = (1/F_{nj})\sum_{f=1}^{F_{nj}} H^{ss}_{fnj2}$ that matters for productivity growth. If firms in an industry are symmetric, this can be approximated by total R&D in an industry and country per $ value added.

[12] In what follows, I suppress time indices if they are not necessary for understanding the context.

Growth is also increasing in parameters measuring the height of innovations, γ, the efficiency in R&D, λ, and the input intensity of the intermediate good in the final good sector, α_{xn}.

2.3.2. Technology transfers and I-O linkages

Assume now that the final good also is used as an input in other domestic industries' final good production. By this set-up, innovations in one industry increase productivity in other industries as they use the first industry's output as an input. The size of the productivity gain from an innovation in industry s on industry n, depends on the height of innovations, γ, and the input coefficient of goods from industry s in industry n, α_{sn}. An innovation may therefore increase productivity more in other industries than in the innovating industry, a finding that applies to the empirical R&D productivity literature.[13] We assume the number of industries, N, to be large such that productivity will rise in a smooth manner. The implied steady state productivity growth rate for industry n in country j will now become dependent not only on R&D performed in the own industry but on R&D in other industries as well. The evolution of productivity will be[14]

$$\mathrm{AGR}_{nj} = \lambda \ln(\gamma) \left[\alpha_{xn} H^{ss}_{nj2} + \sum_{\substack{s=1 \\ s \neq n}}^{N} \alpha_{ns} H^{ss}_{nj2} \right] \tag{10.a}$$

where α_{sn} is the input coefficient of goods from industry s in industry n, and α_{xn} is the input coefficient of the industry-specific intermediate good v_x, in industry n.

2.3.3. Empirical specification

Using Eq. (8), we specify a regression equation and replace growth in the technology index with its corresponding expression derived in Eq. (9). The theoretical model gives a precise prediction of the source of technology growth, namely the number of R&D workers[15]. In the empirical specification, we try some alternative specifications in an attempt to gain additional insights into the mechanism driving technological growth. Finally we note, as motivated above,

[13] See, for example, Griliches (1992).

[14] The solution of the model is given in Appendix 1.

[15] As an alternative to the number of R&D workers as a measure of input on R&D we may use R&D expenditures.

that the right hand side variables in row one in Eq. (8) are suppressed to dummy variables and we write the corresponding regression equation with no technology transfers as

$$\Delta_t \ln r_{njt} = \beta_0 + \beta_1 (R\&D) + \beta_2 \left(\mu_n \Delta_t \ln y_{fnjt}\right)$$
$$+ \sum_{v=1}^{V} \beta_{3v} \left(\alpha_{vn} \Delta_t \ln w_{vjt}\right) + \sum_{t=1}^{T-1} \beta_{4t} D_t + \sum_{n=1}^{N-1} \beta_{5n} D_n + \sum_{j=1}^{J-1} \beta_{6j} D_j + \varepsilon_{njt}. \qquad (11)$$

The βs are coefficients to estimate, r is the coefficient of specialisation (production/consumption), (R&D) is a measure of input in R&D, μ_n captures the degree of increasing returns in industry n, and y_{fnjt} is output of the representative firm. The Hecksher-Ohlin variables are constructed using an interaction of industry-specific intensity parameters, α_{vn}, and the corresponding national factor prices, w_{vj}. Allowing for technology transfers, we add Eq. (10.b) to the regression equation[16]. We may also include inter-industry demand links.

3. Variables

Technology, and technology transfers

Superior technology or know-how in a certain industry generates a competitive edge over competitors. Productivity growth is in the model driven by R&D and generates a Hicks-neutral shift in the production function. In the empirical R&D and technology literature, several R&D measures are proposed when estimating the impact of R&D on market shares or productivity[17].

Following Gustavsson *et al* (1999), we use a set of variables that reflect various aspects of R&D efforts. We apply measures of R&D effort at the national- and industry-level, as well as industries' R&D intensities (R&D per value added). This strategy helps us to analyse what the relevant level of aggregation is[18].

According to our theoretical framework, changes in specialisation may be related both to initial levels of technology gaps, measured by cumulated R&D stocks, as well as to creation of new technology gaps as measured by the current flow of R&D effort. In the regressions, we use both industries' and countries' R&D stocks, $(S)_{njt}$, (S_{jt}), obtained through cumulating the corresponding R&D expenditures. We do not have access to firm level data. A proxy for the firm-

[16] In the regressions, the main diagonal in I-O matrix is set to zero and row standardised such that each row sums to one.

[17] For a survey see Stoneman (1995).

[18] Because of the impact lag of R&D on affecting specialisation, we use lagged averages over three years [average (t-3 to t-1)].

specific R&D stock, $(S)_{fnjt}$, is the industry's R&D stock per value added, $(S/VA)_{njt}$, obtained through dividing the industry-specific R&D stocks, $(S)_{njt}$ with their corresponding value added, VA_{njt}. Given symmetry of firms, this will also reflect the absolute size of the representative firms' R&D stock[19]. The actual number of firms in industries and countries would have been a preferred tool for downscaling of the industries' R&D stocks but we do not have such data[20]. Industries' R&D to value added ratio, are found to be very autoregressive with an autoregressive corr[*(R&D/VA(t), R&D/VA(t-5)*] = 0.86. This autoregressive property makes small deviations from the exact timing of the impact lag of R&D less severe and, the stock and flow R&D measures correlated, i.e., industries R&D stocks per value added are like an upscaled version of their R&D intensities.[21]

An alternative to firms' R&D stocks is the flow correspondence, industries' R&D outlays per value added, $(R\&D/VA)_{njt}$. By the same logic as above, this will reflect total outlays on R&D by the representative firm.

To capture the inflow of technology transfers via deliveries among industries, we utilise national input-output matrices (OECD, 1995b) and row standardise them such that each row sums to one[22]. By row standardising, we are able to interpret the estimated coefficient in economic terms. The matrix V^{in} is then multiplied by the R&D variables[23].

Endowments

The theoretical framework is based on national factor prices w_{vj}. It is difficult to find comparable cross-country time series of factor prices. One way to overcome this problem is to substitute countries' quantities for factor prices. It has been shown that even in higher dimensions, a negative correlation between factor prices and endowments can be established[24]. Gustavsson *et al* (1999) found a negative significant correlation between countries' endowments and national factor prices for factors where both prices and endowments where available. The variables used in the regressions are interaction variables where industries' factor intensities are multiplied by national endowments. A country is expected to have a comparative advantage in industries that use its relatively abundant – and thus cheap- factors intensively. In the production function, for a given industry, factor intensities are assumed to be the same across countries and

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19 For details, see Gustavsson *et al* (1999).

20 We have data on the number of establishments in industries for all countries in the sample at one point in time; this will be used later.

21 The correlation between industries R&D stock per value added and R&D per value added is 0.71.

22 The input-output matrices are available for six countries; for the remaining four countries, the average input-output matrix is used.

23 See Appendix 2 for details.

24 For details, see Ethier, (1984).

constant over time. In the regression variables, Swedish data for factor intensities are applied if cross-country data are not available. In some cases the full panel for intensities are available and therefore used.

Market size effects

In the theoretical model, the μ_n term is a measure of the degree of IRS at the firm level in industry *n,* and is interacted with firm size y_{fnjt}, $\mu_n * y_{fnjt}$. The interpretation is that in industries with strong IRS, countries with large firms have a comparative advantage because of low unit cost. We do not, however, have access to firm level data and therefore, we re-specify this variable to grasp market size effects instead of firm size effects on competitiveness. This relates to the new economic geography literature where the interaction between market size, IRS, and transportation costs generates agglomeration.

We apply a measure of IRS at the firm level for each industry, $\tilde{\mu}_n$, measured as average plant size (Q_{nj}/(number of establishments)$_{nj}$), where Q is the value of gross output. This time invariant measure of IRS is interacted with the corresponding industries' value added q_{njt}, ($\tilde{\mu}_n * \ln q_{njt}$), where q_{njt} is a proxy for industries' market size[25]. We expect the estimated coefficient for this variable to be positive *if* countries with large markets have increased their specialisation in IRS industries. If no concentration or de-concentration occurs, the estimated coefficient will be insignificant or negative.

The derived model gives an expression for the growth of firm size as a relevant regression variable. By the same reasoning as above, we replace firms' output with industry output and the outcome is a variable, [$\tilde{\mu}_n \Delta_t \ln q_{njt}$], that catches the growth rate of market size. If countries with industries significantly increasing output systematically do so because net export in IRS industries has grown faster than domestic demand, this implies a positive sign for the estimated coefficients[26].

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[25] One might question whether the industry or the whole country is the relevant measure of market size. In the literature, there are indications that new firms locate in regions with a large own industry, see Charlton (1983), Rosenthal & Strange (1999) and Head *et al* (1995). That is, the size of the industry seems to be a relevant measure of market size. Wolff (1997) finds that consumer goods, on average, travel longer distances than intermediates. This underscores the importance of backward linkages for firms' decisions regarding where to locate.

[26] Formally, if we define $r_x = r-1$, we have $\dot{r}_x / r_x = \dot{N}x / Nx - \dot{c}/c$. An alternative way to look at the problem is to use that $\dot{r}/r = \dot{Q}/Q - \dot{C}/C$. Hence, if gross output grows faster than total domestic demand we will have a positive correlation between growth in output and the coefficient of specialisation. Potential endogeniety in this variable suggests a careful interpretation of results concerning this 'change' variable.

I-O demand linkages
In the extended version of the model, input-output linkages between national industries are introduced since output from one industry is used as an input in other industries. We attempt to model how changes in demand from other domestic industries affects specialisation and trade patterns. Econometrically, the I-O matrix is multiplied by the growth rate of value added in other national industries.

4. Results

Have countries' initial specialisation patterns become reinforced? We would expect this to happen if transaction costs decrease over time, countries' factor accumulation is such that their factor abundance diverges, or initial technology gaps are reinforced.

In Figure A3.1, changes in specialisation are plotted against initial levels of specialisation. If specialisation has increased over time, observations will be concentrated in the upper right and lower left quadrant of the figure. Such a pattern would imply an increase (decrease) in the coefficient of specialisation for those who are initially net exporters (importers). There is no indication of such a pattern. However, the true patterns may be too complex to be revealed in a simple figure and we will return to this issue.

We start our analysis by using the simple model in Eq. (11) to which additional variables are appended. When studying changes (over a five year interval) we remove industry and country time invariant effects as well as time invariant measurement errors. We can also capture state dependence and dynamic effects of accumulation of productive factors; this is something that is generally impossible in level regressions. Jointly, this may add new insights into what determines the dynamic evolution of trade patterns. Due to missing values, the number of observations is reduced from 880 to 707[27]. The regressions are presented in Table 1. To allow for an impact lag for changes in the independent variables to affect specialisation and to reduce noise, most variables are lagged averages over two to three years[28].

[27] The maximum number of observations is (T=4 * N=22 * J=10)=880.
[28] For details, see Appendix 2.

Table 1. Regression results.
Dependent variable: growth in the coefficient of specialisation (r)

	Mod 1	Mod 2	Mod 2	Mod 4	Mod 5	Mod 6
Variable (Hypothesis)	OLS Robust	GMM-G[B]	GMM-G	GMM-G	GMM-G	GMM-G
$\Delta_t(\alpha_{Hnt}H_{jt})$ Acc human capital	0.1388 (2.09)	0.0754 (2.71)	0.0711 (2.58)	0.0674 (2.46)	0.0714 (2.60)	0.0705 (2.57)
$\alpha^S_{Knt}\Delta_t(K/L)_{jt}$ Acc phys capital	9.2E-09 (2.50)	7.0E-09 (2.61)	7.6E-09 (2.88)	8.8E-09 (3.32)		5.7E-09 (1.68)
$\alpha^B_{Knt}/\ln w_{rjt}$ Initial phys capital					0.0283 (3.52)	0.0191 (1.96)
$\tilde{\mu}_n\Delta\ln q_{njt}$ Growth of M-size	4.2E-09 (2.38)	2.9E-09 (3.74)	2.9E-09 (3.60)	2.8E-09 (3.60)	2.8E-09 (3.50)	2.8E-09 (3.50)
$\ln(\tilde{\mu}_n q_{njt})$ Initial market size					-8.3E-04 (-0.33)	-0.0021 (-0.81)
$(R\&D/VA)_{njt}$ Inv ratio in R&D	0.0015 (2.00)	6.2E-04 (2.30)				
$(S/VA)_{njt}$ R&D stock /plant			2.5E-04 (3.05)	3.1E-04 (3.72)	3.0E-04 (3.62)	3.3E-04 (3.90)
$V^{in}\,(R\&D/VA)_{njt}$ R&D spillovers				0.0020 (2.97)	0.0021 (3.07)	0.0021 (3.10)
$\Delta_t \ln\,(Ex)_{jt}$ Growth in Ex-rate	5.1E-03 (1.98)	3.8E-04 (1.53)	3.8E-04 (1.57)	4.7E-04 (2.08)	4.6E-04 (2.02)	4.7E-04 (2.09)
$V^{out}\varepsilon$ Common shocks		0.2571	0.2653	0.2008	0.1964	0.176
R^2	0.117	0.052	0.052	0.062	0.067	0.069
Sq. corr		0.107	0.097	0.104	0.117	0.118
Obs	707	707	707	707	707	707
LM-test[A]. Type of interdependence p-value: error (lag)	0.000 (0.000)		0.000 (0.000)	0.001 (0.000)	0.003 (0.001)	0.004 (0.001)

Notes: t-value within parenthesis. V = Row standardised I-O matrix. Period dummies and a constant included in all models. An F-test rejected country and industry dummies. OLS model is estimated using White (1980) heteroscedasticity consistent t-statistics.

[A] For GMM models, the error parameter is considered to be a nuisance parameter, in that it helps estimation of other parameters; no t-value is available, therefore we present a separate test for type of interdependence.

[B] -G indicates that the regression is corrected for groupwise heteroscedasticity with respect to country. A LR-test indicates groupwise heteroscedasticity w.r.t. country (significant at all relevant significance levels). In GMM models, R^2 is only indicative; therefore we present the squared correlation as an alternative measure of the goodness of fit.

Table 1. Continued

	Mod 7	Mod 8	Mod 9	Mod 10
	Test of I-O Dependence	Test of IRS in R&D at the firm level		
Variable (Hypothesis)	GMM-G	GMM-G	GMM-G	GMM-G
$\Delta_t(\alpha_{Hnt} H_{jt})$ Acc human capital	0.0751 (2.71)	0.0696 (2.54)	0.0660 (2.46)	0.0679 (2.53)
$\alpha^S_{Kn}\Delta_t(K/L)_{jt}$ Acc phys capital	4.3E-09 (1.26)	5.2E-09 (1.36)	7.8E-09 (1.98)	4.9E-09 (1.45)
$\alpha^B_{Knt} / \ln w_{rjt}$ Initial phys capital	0.0188 (1.91)	0.0193 (1.94)	0.0255 (2.54)	0.0216 (2.23)
$\tilde{\mu}_n \Delta \ln q_{njt}$ Growth of M-size	3.2E-09 (3.91)	3.0E-09 (3.68)	2.8E-09 (3.42)	3.0E-09 (3.71)
$\ln(\tilde{\mu}_n q_{njt})$ Initial Market size	-7.9E-04 (-1.07)	-0.0024 (-0.87)	-0.0020 (-0.72)	-0.0032 (-1.23)
$(R\&D/VA)_{njt}$ Inv ratio in R&D	8.2E-04 (2.93)			
$(S/VA)_{njt}$ R&D stock /plant		3.0E-04 (2.54)	6.9E-05 (0.48)	4.7E-05 (0.32)
$\tilde{\mu}_n$ Average plant size		8.6E-11 (0.13)	-1.1E-09 (-1.42)	
$\tilde{\mu}_n$ $*(R\&D/VA)_{njt}$ IRS in R&D			1.8E-11 (2.74)	1.2E-11 (2.32)
V^{in} $(R\&D/VA)_{njt}$ R&D spillovers	0.0021 (3.03)	0.0021 (3.04)	0.0020 (2.93)	0.0021 (3.14)
V^{out} $(VA)_{jt} \mid r>1$ I-O dependence	-0.0524 (-1.57)	-0.0569 (-1.73)	-0.0552 (-1.70)	-0.0557 (-1.71)
V^{out} $(VA)_{jt} \mid r<1$ I-O dependence	-0.0238 (-0.75)	-0.0278 (-0.89)	-0.0299 (-0.96)	-0.0316 (-1.01)
$\Delta_t \ln (Ex)_{jt}$ Growth in Ex-rate	4.1E-04 (1.78)	3.9E-04 (1.70)	3.9E04 (1.72)	3.6E-04 (1.58)
$V^{out}\varepsilon$ Common shocks	0.187	0.184	0.178	0.177
R^2	0.064	0.064	0.062	0.062
Sq. corr	0.128	0.117	0.113	0.115
Obs	707	707	707	707
LM-test. Type of interdependence p-value: error (lag)	0.006 (0.002)	0.005 (0.001)	0.006 (0.002)	0.006 (0.002)

Market size effects
Concentration and localisation of industries is a subject that recently has received much attention from economists. This is largely due to what has become known as the new economic geography[29]. A central prediction is that as a result of an integration process, industries with economies of scale will become increasingly concentrated in countries with large markets. However, as the integration process proceeds, this concentration will reverse itself.

In the regressions we use two interaction variables to account for this effect, obtained by multiplying a proxy for IRS in an industry with (a) the initial home market size, and (b), the growth of market size.

The growth of the markets size, $\tilde{\mu}_n \Delta_t \ln q_{njt}$, is found to have a positive and significant impact on the evolution of the coefficient of specialisation. The interpretation is that an industry active in a country that significantly increases its output does so because, on average, net exports have grown faster than domestic demand. This can be seen as an outcome of a concentration or reallocation of industries.

The absolute size of the market size, $\tilde{\mu}_n \ln q_{njt}$ never enters with a positive significant estimate (it is actually negative and insignificant). This indicates that we do not have an increased specialisation of IRS industries in countries with large markets.

These results are consistent with Davis & Weinstein (1996) who find scant evidence for economic geography effects in a sample of OECD countries. Forslid *et al* (1999), in a simulation study of European industrial location, find little impact of decreasing transportation costs (integration) on industrial concentration. Amiti (1999) uses changes in Gini coefficients to measure changes in specialisation and finds increased specialisation in six out of ten European countries, and decreased specialisation or no change in the remaining four countries' Gini coefficients. At the industry level, Amiti finds increased concentration in 30 out of 65 industries, and reduced concentration or no change in the remaining 35 industries.

In short, we find no evidence for an increased specialisation of IRS industries in countries with large markets while countries with industries that grow relatively much has increased their specialisation, indicating a reallocation of industrial activity. We might, however, gain additional insights when analysing state dependence in endowments.

Physical capital
The idea that countries with relatively high capital accumulation increase their comparative advantage in capital-intensive industries is supported in the regressions. Investment and capital accumulation may be thought of as a generalised Rybczynski effect, shifting production towards capital-intensive

[29] For a survey of models see Fujita *et al* (1999) or Hanson (2000)).

industries. One may also argue that a high investment ratio in capital upgrades the mean vintage of the capital stock. Since newer machinery is more efficient than older machinery, this improves competitiveness. This is in line with the embodied technical change view of technical progress (Stoneman, 1983). In the regressions, we cannot discriminate between these hypotheses.

In regression models 1-4, we find support for accumulation of physical capital to shift the industry towards increased net export of capital-intensive goods. In regression models 6-10, we control for the initial price of capital when estimating the impact of capital accumulation on specialisation and find the accumulation of capital to still be significant at the ten percent level in two out of five regressions[30]. The reduced significance in the capital accumulation variable might be driven by a positive correlation between these variables[31].

The raw correlation between countries' growth rate in capital per capita and initial capital stock per capita is 0.33, meaning that capital abundant countries have increased their capital stock most.

Gustavsson *et al* (1997) found little support for the accumulation of capital to affect the coefficient of specialisation. Harrigan (1997) found no robust evidence for capital to explain the production structure in manufacturing among a set of OECD countries. On the other hand, capital was found to be an important factor when Davis & Weinstein (1996) analysed production among a set of OECD countries in a nested H-O-V and economic geography model.

In the case of a world with fixed endowments and an ongoing integration process, reducing transportation costs (pure transportation costs, tariffs, red tape, and harmonisation of product standards, etc) between countries would imply increased specialisation according to the initial comparative advantage of countries[32]. In this case, initial endowments alone would be an important determinant of future changes in trade patterns.

Using initial positions, we find in regression models 5-10 that the interaction between industries' capital intensity and the price of capital, (measured as the inverse of the initial return to capital) is a significant predictor for subsequent changes in the coefficient of specialisation[33]. In regression models 6-10, both the accumulation of capital and initial capital prices is applied. This weakens the significance of the rate of capital accumulation while the initial capital price remains significant[34].

[30] The change in the capital stock is not robust to various non-linear transformations. That is, *if* we take logs of capital per capita, the estimated coefficient will generally be insignificant.
[31] The correlation is 0.52, which is a relatively high value.
[32] In a Ricardian model this holds in higher dimensions; but applied to an H-O model, for this to hold in higher dimensions (compared to the 2x2x2 model) we must add some assumptions, for details see Ethier (1984), p135-40.
[33] For initial positions, we use a measure of the price of capital since this is in line with the theoretical model; the results do not depend on what measure we apply (price or endowment).
[34] The raw correlation between countries' return to capital and capital abundance is -0.70, meaning that in capital-abundant countries the price of capital is low.

Jointly, these results indicate that even after controlling for capital accumulation countries with initially cheap capital (capital-abundant countries) have shifted their industrial structure towards increased net export of capital-intensive goods. This increased concentration of *capital-intensive* industries into capital-abundant countries could be an effect of European integration. Finally, there is evidence for capital accumulation to be higher in capital-abundant countries, emphasise the concentration of capital-intensive industries in capital-abundant countries.

Amiti (1999) gives both a survey and analyses changes in European specialisation patterns. She finds increased concentration in high IRS industries. To the extent that high IRS industries are positively correlated with capital intensity, our results are similar[35].

Human capital

Human capital and its importance for productivity growth is stressed in the endogenous growth literature.[36] In a Heckscher-Ohlin framework, endowments and accumulation of immobile factors determine changes in industrial structure and trade patterns. Empirically, labour is a rather immobile across nations even though domestic mobility may be high. Independently of what view one believes (the factor proportion theory or the endogenous growth approach), uneven accumulation of human capital across countries will impose changes in countries' specialisation patterns. In the regressions, human capital enters as an endowment.

The econometric results support the hypothesis that countries with a high *accumulation* rate of human capital tend to increase their specialisation in human capital intense industries[37].

If we apply initial levels of human capital the estimated parameter is insignificant (estimations available on request). That is, countries that were initially human capital abundant have not significantly changed their specialisation in human capital intensive industries.

We find the correlation between initial levels of human capital and the accumulation rate of human capital to be –0.37[38]. The interpretation is that there is a tendency towards convergence, i.e., countries with a low supply of skilled labour are catching up with human capital abundant countries.

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[35] In Table A3.4, the correlation between industries capital intensity and degree of IRS is found to be 0.37 with a p-value of 0.09.

[36] See Romer (1990), Aghion & Howitt (1992), and Grossman & Helpman (1995), for example.

[37] In the regression, we use changes in the average years of schooling for population > 25 years as an accumulation measure (data from Barro & Lee, 1993). Another proxy for countries' endowments of skilled labour is percent higher education attained or completed. Using any of these measures generates basically the same econometric results; these results do not depend critically on endowments being estimated using non-logs.

[38] The relevant variable is ln(average years of schooling, population older than 25 years).

Exchange rates
All variables analysed above mirror changes in real variables. It might however be argued that changes in trade patterns in the short run are tied to monetary fluctuations. A crude measure of monetary distortions is the relative change in the exchange rate (national currency per USD). The expected sign of this variable is positive since a depreciation of the exchange rate makes export goods relatively cheaper. In the estimations, we find this variable to be positive and significant at the ten percent level in seven out of ten models, with estimated parameters running from 0.00036 to 0.0051. That is, a depreciation of 10% relatively to the USD over a five year interval is expected to increase the growth in the coefficient of specialisation by 0.0038-0.05 percentage points over five years.

R&D
The absolute size of R&D expenditure as a source of productivity growth and increased competitiveness is stressed in various endogenous growth models[39]. When analysing the impact of R&D on competitiveness, one prominent question is what the relevant measurement unit is: the *firm*, the *industry* or the *nation*?

If each firm is producing a differentiated product with largely product specific output from its own R&D, and technology transfers are small, the firm level is the appropriate unit of measurement when measuring the impact of R&D on productivity, competitiveness, and trade. In the case where all firms are of the same size, the ratio of an industry's total R&D to value added also reflects the absolute level of firms' resources allocated to R&D by the representative firm.

In regression models 1, 2, and 7, the R&D intensity (*R&D/VA*), is used. According to the OLS estimate in regression model 1, a ten percentage units higher industry R&D investment ratio over a five year period in an industry boosts the five year growth in the coefficient of specialisation by 0.015%.[40]

If we replace the flow measure, i.e. industries' investment ratios in R&D, with a proxy for the size of the R&D stock of the representative firm, $(S/VA)_{njt}$, measured as the industries' R&D stock per value added, we again find a positive and significant impact of R&D on the growth rate in the coefficient of specialisation, r.

In regressions not presented here industry-specific (S_{njt}), and national R&D stocks (S_{jt}), were used. These *never* generated a positive and significant impact on growth in the coefficient of specialisation, no matter how the regressions were specified. This is consistent with the hypothesis that what matters for

[39] See, for example Aghion (1992), Romer (1990) or Young (1998) for a model without scale effects, and a discussion.
[40] To reduce noise and lag sensitivity a three year, lagged average is used. See Appendix 2 for details.

competitiveness is the R&D effort of the representative firm, rather than the total R&D expenditures in the industry, where the per firm variables are measured by the industries' ratio, R&D per value added, and industries' R&D stock per value added. To some extent, this contradicts Gustavsson *et al* (1999) where large industry and national R&D stocks generated positive effects in explaining the *level* of specialisation.

In Table A3.1 we note that industries investment ratio of R&D to value added and firms' R&D stock per valued added are correlated [corr($(R\&D/VA)_{njt}$, $(S/VA)_{njt}$) = 0.71]. That is, in industries with high R&D investment ratios we observe firms with large R&D stocks. This positive correlation might to some extent be driven by the way the earlier detected autoregressive property of R&D investments.

If we have scale effects in R&D at the firm level, large firms will have an edge over small firms. In regression models 8-10, we investigate scale effects in R&D. In regression model 8, the variables plant size, $\tilde{\mu}_n$, and R&D, $(S/VA)_{njt}$ are applied.[41] We find no significant plant-size effects while the effect of R&D is both positive and significant. In regression model 9, the interaction effect between R&D and plant size, $\tilde{\mu}_n * (S/VA)_{njt}$, is added. The interaction variable is positive and strongly significant while the own effect of R&D and plant size is insignificant. The interaction term overtakes the own effect of R&D. These results suggest scale effects in R&D at the firm level. This is in line with results in Gustavsson *et al* (1999), (when analysing the level of industrial specialisation).

Technology transfers

So far, changes in competitiveness of industries have been assumed to be independent of each other. There are several ways in which changes in industries' specialisation may be interdependent.

First, technical progress in one industry may not only be driven by its own R&D, but also by R&D in other industries. Technological transfers may be proportional to how intensively the receiving industry uses output from the innovating industry. That is to say, technology transfers are expected to be forward links – from suppliers to users-. The strength of the links is measured by the elements in the V^{in} matrix.

Second, there may be domestic, inter-industry demand linkages, affecting the relative size of the home market and, through this mechanism, industries specialisation. In this case we expect the supplier to be dependent of its users, that is, backward linkages are assumed to be what matters. One could however, imagine that forward linkages also matters for I-O dependence, since in this

[41] Because of lack of firm level data we use plant size to proxy firm size. Given full symmetry this is appropriate. The true distribution is, however, unknown. This motivates a careful interpretation of the results.

case, changes in one industry's demand affect its suppliers as well. In analysing I-O demand links we, however, focus on the backward linkages, captured by the V^{out} matrix.

Third, there may be some kind of general interdependence in the error term (or in the dependent variable), where the interdependence may be proportional to the strength of the I-O links connecting industries. By the same logic as for the I-O links we concentrate on the backward linkages, that is, user demand is what measure closeness of suppliers to users. To be precise, for one industry, what matters are what happen in other industries' where the dependence are proportional to its I-O links, measured by the elements in the V^{out} matrix. Each of these three types of interdependences will be analysed.

When analysing national inter-industry technology spillovers, we assume the impact of other industries' R&D to be proportional to the input coefficient in the receiving industry's final good production. This is consistent with viewing trade as a carrier of technology transfers and in line with Keller (1997) and Coe & Helpman (1995), for example[42].

In regression models 4-10, the input-weighted R&D intensities in other national industries $[V^{in}(R\&D/VA)_{njt}]$[43] is introduced as a regressor. We find a positive and significant impact of the weighted R&D intensities in other national industries on the growth rate in the coefficient of specialisation in the receiving industry. The estimated coefficient is close to 0.002 in all models. The interpretation for an industry is that an increase in the weighted average of R&D intensities in other industries of one percentage point over a five year period increases growth of the coefficient of specialisation by 0.002%.

In regressions not presented here (available on request), the proxy for firm-specific R&D stocks $[V^{in}(S/VA)_{njt}]$, were applied. Generally, the significance was weaker. Industries total R&D stock $[V^{in}(S)_{jt}]$ turned out to be irrelevant for technology transfers.

The results indicate small inter-industry transfers and that industries' R&D intensities' or firms' own R&D, (and not the industries total spending on R&D) is what matters for increased competitiveness. Combined with scale effects in R&D at the firm level, this is good news for small countries that may spend relatively little on R&D at the industry level but may have a few large firms with large R&D departments generating new technology and technology transfers. Thus the disadvantage of being part of a small economy, as some theoretical models predict, is not supported in these data. These results are in line with Keller (1997) who examines the transmission of technology and finds the impact of domestic inter-industry and foreign same industry R&D to be in the range 0.2-0.5, 0.5-0.95 respectively relatively to own R&D when explaining productivity levels.

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[42] Coe and Helpman, however, studies cross-country technology transfers.
[43] The main diagonal of the weight matrix, V, is set to zero since we want to exclude the impact of own R&D.

Common shocks

The question we analyse in this section is: If an industry is hit by a positive shock and experiences a higher net export ratio than predicted by the independent variables, will other domestic industries that are relatively large customers, also experience a positive shock?[44] This question may be answered by means of spatial econometric techniques where we replace the usual distance measure with I-O trade weights.

In the analysis, we use the national I-O matrices to measure how close industries are to each other. If industries are interdependent and move together in clusters, where the I-O matrix measures the distance between industries, this will result in an interdependent error term[45]. Formally, this is modelled as $\varepsilon = \varphi V^{out} \varepsilon + \eta$ where φ is a parameter to estimate, V^{out} is the block diagonal [N'*J*T,N*J*T] I-O delivery matrix, η is a [N*J*T, 1] white noise vector, and ε is the original vector of errors[46].

The econometric results strongly support the hypothesis that industries experience common shocks. The estimated coefficient is in the interval 0.18-0.26. The interpretation of a coefficient of 0.25 is that if an industry's neighbours are hit by a weighted shock of λ units we expect the industry to experience a shock of $0.25{*}\lambda$ units.[47] That is, a shock fades out as it is propagated across industries.

As a test of robustness and the nature of interdependence, we re-formulate the GMM-G models to a 'spatial lag model'. That is, we substitute the interdependence in the error term with an interdependent dependent variable, ($V^{out}{*}\Delta_t\, r$), and estimate the model by means of 3SLS. A generalised model is then $y = \rho Wy + xB + \eta$ where y is the dependent variable, W is the (row-standardised) weight matrix, ρ is a spatial lag coefficient to estimate, and η is white noise. By using IV techniques, the estimated coefficient measuring I-O interdependence is no longer bounded to one from above. In estimations (available on request), the estimated spatial lagged coefficient is roughly in the range 0.9-1.1 and always positive and significant at all relevant significance levels. Hence, the robustness of interdependence does not hinge on a particular specification of the nature of interdependence. On the other hand, the exchange

[44] By this, we relax the usual econometric independence assumption.

[45] The implication of a non-independent error term is like a non-spherical error, and OLS yields unbiased parameter estimates but biased parameter variance. If the interdependence is in the dependent variable and not controlled for, this generates an omitted variable bias.

[46] The error dependence models are estimated using the Kelejian & Prucha (1999) GMM estimator. For an introduction and survey of spatial econometric models, see Anselin (1988). All regressions are performed using SpaceStat, Anselin (1995).

[47] This straightforward interpretation is only possible when the I-O matrix is row-standardised such that each row sums to one. This row-standardisation puts an upper bound on the coefficient of one.

rate variable and some of the other independent variables turn from being positive and significant to insignificant when $(V^{out}*\Delta_t r)$ is used. This may been seen as an effect of reduced efficiency when using IV techniques. There is, however, robust evidence for interdependent industries.[48]

Domestic inter-industry demand links

How do changes in demand from other domestic industries affect specialisation patterns?

The expected impact of increased demand from other domestic industries is a movement towards autarky and thus a value of one in the coefficient of specialisation. We multiply the I-O delivery matrix V^{out}, by the vector of growth rates in industries value added, Δ_t lnVA, and condition this on a dummy for the level of the coefficient of specialisation r, being above or below one. This gives us $V^{out}(\Delta_t \ln VA)|r>1$, and $V^{out}(\Delta_t \ln VA)|r<1$ as the relevant variables.

For industries with an initial value in the coefficient of specialisation above (below) one, the expected sign of the variable is negative (positive). In regression models 7-10, these variables are applied.

The results are non-symmetric. For initial values above one for the coefficient of specialisation, we have (as expected) an estimated negative coefficient significant at the ten percent level in three out of four models. When we condition on initial values in the coefficient of specialisation below one, the estimated coefficient has the wrong sign (a negative sign) and is insignificant. This slight significance may be due to industries generally having a low degree of dependence on demand from other domestic industries (compared to foreign and other domestic demand). There may also be imperfect data and variables. Note that the estimates measuring technological transfers and error interdependence are basically unaffected when introducing domestic I-O demand links. This is a link that has not previously been explored this way and a potential avenue for future research in understanding the magnitude of industrial home market demand effects.

Other variables

A set of other H-O variables, not presented in Table 1, was used in the regressions. None of them turned out to have a significant impact on changes in specialisation, no matter if they were used in levels or in changes. The variables were arable land per capita, multiplied by a dummy for industry 31 (food), production of *electrical energy* per capita, multiplied by energy cost per employee in industry n, and finally *forest land* per capita, multiplied by input of roundwood per 10 000 SEK output in industry n. In Gustavsson *et al.* (1997,

[48] Considering efficiency properties of the IV estimations and the non-bounded parameter estimate of interdependence when using IV techniques makes the GMM estimations preferred.

1999), these variables were found to be important determinants for the level of specialisation. These variables do not change by much over time and do not add much in explaining changes in trade patterns.

5. Conclusions

In this paper we analyse changes in countries' specialisation patterns. A trade model that embeds factor prices (endowments), technology, and effects from increasing returns to scale, is derived. We allow industries to be interdependent through technology transfers, inter-industry demand linkages, and a general interdependence working through the error term. Using a quality ladder model, technological progress and technological transfers are made endogenous. In the econometric analysis we also study how changes in specialisation are related to countries' factor abundance (level, or state dependence). Level dependence as a determinant for future changes in trade patterns is an avenue for future research.

We analyse ten European countries, and 22 manufacturing industries according to the ISIC (rev 2) classification spanning five year intervals from 1976 to 1996.

The econometric analysis gives no support for a concentration of IRS industries in countries with large markets. Taking this analysis one step further we analyse the impact of accumulation and state dependence in human and physical capital.

We find that a high accumulation rate of physical capital turns the industry towards increased net export in capital-intensive industries. This might partly be seen as a shift in the age composition of the capital stock[49] and partly as a Rybczynski effect.

We also find state dependence in the countries' capital prices (capital abundance), such that countries with initially cheap capital (capital abundant countries) have, on average, increased their specialisation in capital-intensive industries. Capital-abundant countries have also had the highest growth rates in their capital stock. This is an indication of an ongoing concentration of capital-intensive industries in capital-abundant countries.

For human capital, we find (as for capital) that countries with a high accumulation rate of human capital have shifted their trade towards more net exports in human capital intensive industries. There is, however, no indication of increased concentration of human capital intensive industries; rather, there is convergence in that we find a negative correlation between countries' initial endowment of human capital and growth in the human capital stock.

[49] Given that newer machinery is more efficient than older machinery this shifts out firms' production possibility frontiers.

Analysing the impact of R&D on competitiveness, we find no evidence whatsoever for the absolute size of industries' or countries' R&D stocks to have any impact on competitiveness and changes in trade patterns.

On the other hand, we find a positive and significant impact of R&D in industries with high R&D intensities. This holds for both; R&D stock per value added and its flow correspondence, R&D expenditures per value added. Given symmetric firms, these measures reflect various aspects of the amount of resources allocated to R&D by the representative firm. We may take this, as an indication of R&D at the firm level is what matters for productivity growth and increased competitiveness[50].

Investigating scale effects in R&D at the firm level, we interact a proxy for firms' R&D effort with industries' average plant size. Using this variable in the econometric analysis gives robust support for scale effects in R&D at the firm level. That is, we find a positive and significant impact on changes in trade patterns from the interaction term, controlling for the own effects of R&D and plant size.

National inter-industry technology transfers are analysed using national I-O tables as a weighting matrix. Positive and significant inbound R&D transfers are detected when using industries' investment ratios in R&D. No technology transfers are found when using the size of industries' R&D stocks. The relatively small coefficient on technology spillovers emphasises that firms' own R&D is much more important for competitiveness than R&D performed in other domestic industries.

Instead of taking the traditional route of treating observations as independent of each other we relax this assumption and allow for interdependence in the error term. The working hypothesis is that industries that trade a lot with each other are 'close to each other' and hit by common shocks. This makes them move together in a clustered fashion.

In the regressions, there is robust evidence for common shocks across industries. This shock fades out as it is propagated out across industries. Hence, the traditional route of treating industries as independent may be misleading.

In analysing the impact of changes in domestic inter-industry demand, we find weak evidence for this to affect specialisation, and conclude that inter-industry demand linkages are of second order. How changes in domestic inter-industry demand affect specialisation is, however, an unexploited avenue of research.

Exchange rate fluctuations are found to affect trade patterns in that a depreciation of the currency boosts growth in the coefficient of specialisation.

As a remark, we note that even though an almost fully-fledged trade model is applied, we end up with an indicative R^2 and squared correlation of only 5-7%

[50] As it turns out, the correlation between the proxy for firms' R&D stock, $(S/VA)_{njt}$, and the investment ratio in R&D, $(R\&D/VA)_{njt}$, is high: corr[(*R-inv*), (*R-stock(f)*)] = 0.71. This is natural since a large R&D stock is the outcome of firms making large R&D investments.

and 10-13%, respectively. This might appear to be a bit disappointing since level studies often have an R^2 of 40-70 percent (sometimes even higher). However, one should keep in mind that fixed effects, which here are differenced out, drives much of the R^2 in level studies. On the other hand, taking changes allows us to analyse potential level dependence. In summary, we found that domestic industries are interdependent, no evidence of market size or geography effects and that accumulation of productive factors and R&D at the firm level matters for changes in the European countries specialisation patterns.

Appendix 1

Solution and steady state properties of the R&D part of the model

In what follows, the main groundwork is from Aghion & Howitt (1992). For details, see the original article. We focus on steady state properties of the model and constant endowments. By way of S-D-S demand and a Cobb-Douglas production function the final goods sector in industry n will have the following first order condition for profit maximisation with respect to the industry specific intermediate good v_{xnj}, (time subscripts suppressed).

$$w(i)_{xnj} = \frac{\sigma_n - 1}{\sigma_n} p(i)_{nj}^F \alpha_{xn} \frac{y(i)_{nj}}{v(i)_{xnj}}. \qquad \text{(A1.1)}$$

The simple linear technology in the IG sector and profit maximisation yields, using Eq. (A1.1), the following price of the intermediate good

$$w(i)_{xnj} = \frac{1}{\alpha_{xn}}\left(\frac{\sigma_n}{\sigma_n - 1}\right) w(i)_{njH}. \qquad \text{(A1.2)}$$

The price of the intermediate good is, as in the original set-up, a constant mark-up over the return to human capital, $w(i)_{njH}$. The additional term here is the elasticity of demand term, σ_n. As expected, the mark-up is inversely related to the elasticity of demand, me: sured by the sigma terms.

As with the price of the intermediate good, return to human capital and productivity all grow at the same rate. The risk-adjusted discounted value of profits for an active intermediate firm with an infinite patent $V(i+1)_{nj}$, equals

$$V(i+1)_{nj} = \frac{\Pi_{nj}^I(i+1)}{r + \lambda H_{nj2}^{ss}}. \qquad \text{(A1.3)}$$

H^{ss}_{nj2} is the steady state (SS), level of human capital allocated to R&D. For an R&D firm the simple first order condition yields

$$V(i+1)_{nj} = \frac{w_{njH}(i)}{\lambda}. \qquad \text{(A1.4)}$$

In the free entry equilibrium, Eq. (A1.3) = Eq. (A1.4). Making some substitutions gives the following expression for the steady state level of resources allocated to R&D in industry n and country j.

$$H^{SS}_{nj2} = \frac{\left(\dfrac{\sigma_n(1-\alpha_{xn})+\alpha_{xn}}{\alpha_{xn}(\sigma_n-1)}\right)\gamma^{\alpha_{xn}} H_{nj} - r/\lambda}{1+\left(\dfrac{\sigma_n(1-\alpha_{xn})+\alpha_{xn}}{\alpha_{xn}(\sigma_n-1)}\right)\gamma^{\alpha_{xn}}} \qquad \text{(A1.5)}$$

The steady state solution for the allocation of human capital between R&D and IG production is basically the same as in Aghion (1992) with the sigmas entering as additional terms. The amount of human capital allocated to R&D and productivity growth is *negatively* related to the elasticity of substitution, σ_n. This is because a high elasticity reduces the mark-up on the intermediate good and therefore increases demand for it, meaning that human capital is allocated away from R&D to intermediate good production, which in turn reduces growth.

Introducing I-O links and technology transfers

When introducing I-O links and technology spillovers, most of the results from the simple set-up remain. For the final good sector, compared to the set-up with no technology transfers nothing happens with the maximisation problem. The interesting change occurs in the intermediate good sector whose active IG plant now faces an increasing profit flow during the patent time, due to innovations in other industries driving up the VMP and the price of the intermediate good. It is convenient to let z denote the state of technology and i the generation of innovation in the own industry. If we let the number of industries N be large, the productivity index z will increase in a smooth manner while the innovation index i, for a single industry moves up less frequently. The expected step size in innovations for an intermediate good producer in industry n during the patent equals

$$E\left[\gamma^{\alpha_{xnj}}\right] = \gamma^{\left(\sum_{\substack{l=1\\ l\neq n}}^{N} \frac{H^{ss}_{lj2}}{(H^{ss}_{j2}-H^{ss}_{n2})}\alpha_{xlj}\right)} \equiv \gamma^{\bar{\alpha}_{xnj}}. \qquad \text{(A1.6)}$$

The expected innovation increases the profit flow in industry n by a factor of $\gamma^{\tilde{\alpha}_{jnx}}$ and the expected time between innovations, during the patent time, in other industries is $1/\lambda\tilde{H}_{j2}^{ss} = 1/\lambda(H_{j2}^{ss} - H_{nj2}^{ss})$. The expected profit flow for an active intermediate good plant evolves according to $\Pi^I(z(t)) = \Pi^I(0)\exp(\lambda\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\lambda t)$. In order to have a finite present value of profits we impose parameter restrictions or a finite patent time. We choose the latter since it is more realistic. Given a T-period patent time, the current value of holding the $(i+1)$ generation of designs is

$$V(i+1) = \Pi(i+1)_0^I \int_0^T e^{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss})-r]t}\,dt \tag{A1.7}$$

$$V(i+1) = \Pi(i+1)_0^I \frac{\exp\{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss})-r]T\}-1}{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss})-r]} \tag{A1.8}$$

were $(i+1)_0^I$ is the beginning of period $i+1$ (or equivalently, the end of period i). Given that $T > 1/\lambda H_{nj}$, the expected number of innovations during the patent time is $\tilde{Z}_{nj} \equiv H_{j2}^{ss}/H_{nj2}^{ss}$ and the expected relationship between profit at the beginning and at the end of the patent time is $\Pi^I(i+1) = \Pi^I(i)e^{\tilde{\alpha}_n \ln\gamma \tilde{Z}_{nj}}$. For the R&D sector, the same profit maximisation problem as in the simple model applies.

$$V(i+1) = \frac{w_{njH}(i)}{\lambda}. \tag{A1.9}$$

In the free entry equilibrium, we have the following steady state solution:

$$1 = \lambda\frac{\sigma_n(1-\alpha_{xn})+\alpha_{xn}}{\alpha_{xn}(\sigma_n - 1)}\gamma^{\tilde{\alpha}_{nj}\tilde{Z}_{nj}} * \tag{A1.10}$$

$$\frac{e^{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss})-r]T}}{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss})-r]}(H_{nj}^{ss} - H_{nj2}^{ss}).$$

The finite time patent makes a closed form solution for the industries' allocation of human capital to R&D H_{nj2}^{ss} non-viable. The new aspect in this section is how innovations in other industries affects IG firms' profit flow.

Average growth rate

For the simple model, we have $A(i)_{nj} = A(0)_{nj}\gamma^{\alpha_{xn}i}$. The expected time E($dt$) passing during the patent time is E[$di=1$] $\Rightarrow dt = 1/\lambda H_{nj2}$ or equivalently di/dt = λH_{nj2}. Integrating both sides gives $i(t) = \lambda H_{nj2}t$. Substitution of i gives

$A(i)_{nj} = A(0)_{nj} e^{\ln \gamma \alpha_{xn} \lambda H^{ss}_{nj2} t}$. The growth rate is then easily found, as stated in Eq. (9). For the extended model, a similar approach is used.

Appendix 2

Data and Variables

Raw data for most country-specific variables is annual observations spanning 1976-96. The regression variables are based on changes over five years.

Coefficient of specialisation

$$r_{njt} = \frac{Q_{njt}}{C_{njt}} = \frac{Q_{njt}}{Q_{njt} + X_{njwt} - M_{nwjt}}$$

Q_{njt} Gross output, industry *n*, country *j*, year *t*, average (*t-1*)-(*t+1*).

X_{njwt} Export, from industry *n*, country *j* to the rest of the world *w*, year *t*, average (*t-1*)-(*t+1*).

M_{nwjt} Import, to industry *n*, country *j* from the rest of the world *w*, year *t*, average (*t-1*)-(*t+1*). Source: OECD (1998).

Skilled labour (accumulation)

$\Delta(\alpha_{Hnt} H_{jt})$

α_{Hnt} Share of human capital in value added, industry n, average over all countries.

α_{Hnt} $l_{nt}(W^s_n / W_n)$

l_{nt} Labour share in value added, industry *n*, year *t*, average over all countries *J*, year *t*, average *(t-1)-(t+1)*. Source: OECD (1998).

(W^s_n / W_n) Skilled labours' wage share, Sweden 1990. Source: SCB Regional Labour Statistics.

H_{jt} Average years of schooling of total population, country *j* year *t*, lagged six years. Source: Barro & Lee (1997).

Physical Capital

$\alpha^{S}_{Kn}\Delta K_{jt}$ and $\alpha^{B}_{Knt} / \ln w_{rjt}$

α^{S}_{Kn} Capital cost per employee, industry *n*, Sweden 1985. Source: SCB, Unpublished data.

K_{jt} Capital stock per manufacturing worker country *j*, year *t*, lagged two years. Source: Easterly & Levine (1999).

α^{B}_{Knt} Cost share of value added to capital, industry *n*, country *j*, $(VA\text{-}wL)_{njt} / VA_{njt}$, year *t*, *t* taken as average (*t-1*)-(*t+1*). Source: OECD (1998).

w_{rjt} Average return to capital [(VA-wL)/K], country *j*, year *t*, lagged two years. Source: OECD (1998), Easterly, W & Levine, R. (1999).

When using levels, initial level in each period is used.. Since we lack manufacturing capital stocks for Spain, we use national capital stocks instead (and thus can keep Spain in the model). The correlation between national and manufacturing capital stock is 0.9645 for the remaining nine countries (1985) and we conclude that what capital stock we use is not a critical issue.

Market size effects

$\ln(\tilde{\mu}_n q_{njt})$ and $\tilde{\mu}_n \Delta \ln q_{njt}$

$\tilde{\mu}_n$ Degree of increasing returns measured as average plant size over all countries in industry *n*, 1989.

$\tilde{\mu}_n$ $1/J \sum_{j \in J} \left(q_{njt=-89} / F_{nj}\right) q_{njt=1989}$.

F_{nj} Number of establishments, industry *n*, country *j*, year 1989. Source: OECD (1995a).

q_{njt} Value added 1990 constant prices, PPP USD 1985, industry *n*, country *j*, year *t*, taken as average year *t* to *t-2*: Source: OECD (1998).
When using levels, initial level in each period is used.

Industries' R&D investment, proxy for firms' R&D outlays

$(R\&D/VA)_{njt}$ Ratio of R&D investments to value added, taken as average *t-3* to *t-1*.

$(R\&D/VA)_{njt} = 100^* (R\&D)_{njt}/(q)_{njt}$.

$(R\&D)_{njt}$ Expenditures on R&D, industry *n*, country *j*, year *t*.
Source: OECD (1999)

q_{njt} Value added industry *n*, country *j*, year *t*: Source: OECD (1998).

Industries' R&D stock per value added, proxy for firms' R&D stock
(S/VA) $= S_{njt}/q_{njt}$, average over three lagged years.
S_{njt} Knowledge capital (R&D) stock, industry *n*, country *j*, year *t*, USD, PPP –85, 1985 prices. For details, see Gustavsson *et al* (1997).

Growth rate in the exchange rate
$\Delta ln\ Ex$ Growth rate in the exchange rate $(\text{currency(j)} / \text{USD})_t$. The value for each period is the average over two years. Source: OECD (1998).

Matrices V^{in} and V^{out}
V National input output coefficient matrix for 1985 (1986 for some countries). For four countries, no I-O matrix is available so the average I-O matrix is imposed on these countries (Fin, Nor, Spa, and Swe). *Out* denotes delivery from industry *n* to other industries. The *in* matrix is the transpose of the *out* matrix and denotes deliveries from each of the other industries to industry *n*. The main diagonal is set to zero and each matrix is row standardised such that each row sums to one. Source: OECD (1995b)

National industry I-O links
$V_j^{out}(VA)_{jt} | r_{nj} < 1$ *and* $V_j^{out}(VA)_{jt} | r_{nj} > 1$
V_j^{out} National I/O matrix. Source: OECD (1995b)
$(VA)_{jt}$ Vector of value added from domestic industries, country *j*, Source: OECD (1998).
$|r_{nj} \geq 1$ and $|r_{nj} < 1$. Dummies = 1 if the initial level of the coefficient of specialisation is larger than (smaller than) 1 respectively.

Technology transfers
$V^{in} * (R\&D/VA)_{njt}$
V^{in} I-O coefficient matrix for inputs from other domestic industries. The main diagonal is = 0.
$(R\&D/VA)_{njt}$ Industries' investment ratio in R&D to value added.

Variables not presented in regressions

$\alpha_{Sn}F_{jt}$ *forest*

α_{Sn} Input of roundwood SEK per 10 000 SEK output, industry n, Sweden 1985. Source: SCB Input-Output Table for Sweden 1985.

F_{jt} Hectare of forest land per capita, country j, year t. Source: SCB, Statistical Yearbook, various issues.

$\alpha_{En}(EL)_{jt}$ *energy*

α_{En} Cost of electrical power SEK per employee, industry n, Sweden 1989. Source: SOS Manufacturing 1989.

$(EL)_{jt}$ Production of electrical energy, country j, year t. Source: SCB, Statistical Yearbook, various issues.

$\alpha_{an}A_{jt}$ *arable land*

α_{an} Dummy variable for industry ISIC 31 (food).

A_{jt} Hectare of arable land per capita, country j, year t. Source: SCB, Statistical Yearbook, various issues.

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SCB, Capital cost per employee by industry, Sweden 1985. Unpublished data.
SCB, input-output table for Sweden 1985.
SCB, Regional Labour Statistics. Unpublished data on employees by industry and level of education
SCB, SOS Manufacturing 1989, Part I.
SCB, Statistical Yearbook of Sweden. Various issues.

Appendix 3

Tables and figures

Fig A3.1. Initial level and growth in the coefficient of specialisation

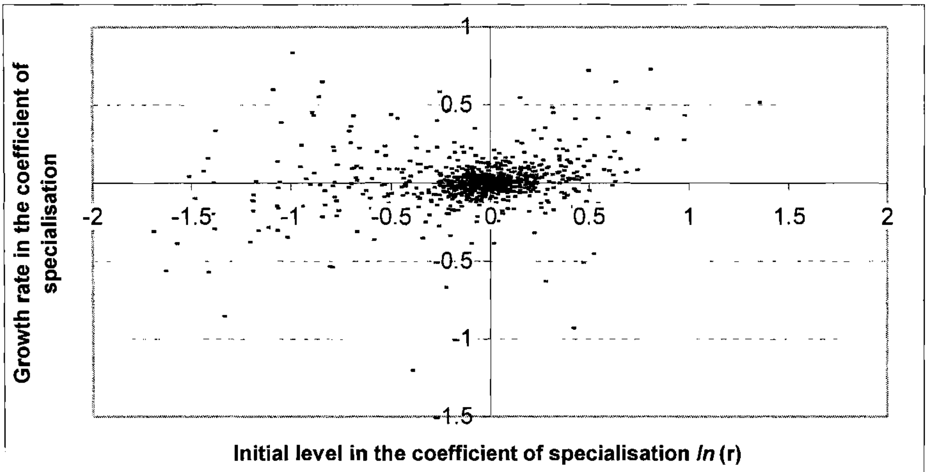

Table A3.1. Correlation Matrix.

	Δ ln r	$\Delta\alpha_{nH}$ H	$\Delta\alpha_{nK}$ K	α_{nK} K	ΔMsize	Msize	R&D/VA	S/VA	ΔlnVx
Δln r	1								
$\Delta\alpha_{nH}$ H	.062	1							
$\Delta\alpha_{nK}$ K	.039	.008	1						
α_{nK} K	.111	.012	.519	1					
ΔM-size	.071	-.215	.090	.092	1				
M-size	-.110	.048	.139	.033	-.147	1			
R&D/VA	.165	-.082	-.139	-.021	.158	.165	1		
S/VA	.113	-.013	-.165	-.052	.096	-.037	.707	1	
ΔlnVx	.087	-.161	-.116	-.011	.032	.007	-.029	-.037	1
V* R&D/VA	.060	.070	.033	-.100	-.044	-.271	-.129	-.106	-.087

Table A3.2. Industries' factor intensities and IRS

Industry	ISIC Rev(2)	IRS[A] (rank)	K/L (rank) intensity	H/L(rank) intensity
Food, drink, & tobacco	3100	43 (11)	69 (10)	6 (20)
Textiles, footwear, & leather	3200	17 (22)	37 (16)	5 (21)
Wood, cork, & furniture	3300	18 (21)	86 (5)	4 (22)
Paper and Printing	3400	34 (15)	128 (3)	11 (11)
Chemicals	351+352-3522	110 (5)	81 (7)	11 (10)
Pharmaceuticals	3522	137 (3)	87 (4)	29 (1)
Petroleum Refining	353+354	300 (2)	327 (1)	6 (19)
Rubber and plastic products	355+356	28 (17)	42 (14)	7 (14)
Stone, clay, & glass	3600	31 (16)	76 (8)	7 (16)
Ferrous metals	3710	92 (8)	159 (2)	8 (12)
Non-ferrous Metals	3720	68 (9)	85 (6)	7 (15)
Fabricated metal products	3810	25 (18)	41 (15)	6 (17)
Office machinery & computers	3825	106 (6)	33 (17)	23 (3)
Non-electrical machinery	382-3525	25 (19)	72 (9)	14 (8)
Electronic equipment & components	3832	93 (7)	31 (18)	24 (2)
Electrical machinery	383-3832	37 (14)	23 (19)	16 (6)
Shipbuilding	3841	38 (13)	66 (11)	14 (7)
Motor vehicles	3843	116 (4)	46 (12)	13 (9)
Aerospace	3845	360 (1)	6 (22)	23 (4)
Other transport equipment	3842+3844+3849	49 (10)	9 (21)	8 (13)
Instruments	3850	39 (12)	13 (20)	21 (5)
Other manufacturing	3900	20 (20)	45 (13)	6 (18)

[A] IRS measured as average plant size, defined as industry VA / No of establishments; average over all countries.

Table A3.3. Endowments

	K/L (rank)	Edu * (rank)
Denmark	17 (3)	10.5 (1)
Finland	21 (2)	9.4 (2)
France	15 (5)	6.4 (8)
Germany	14 (6)	8.6 (4)
Italy	12 (8)	5.8 (9)
Netherlands	13 (7)	8.3 (6)
Norway	23 (1)	7.6 (7)
Spain	8 (10)	5.6 (10)
Sweden	17 (4)	9.4 (3)
United Kingdom	9 (9)	8.4 (5)

*Average years of schooling pop > 25 years, 1985.

Table A3.4. Correlation of industry intensities

Variable (p-value)	IRS	Capital
IRS	1	
Capital	0.37 (0.09)	1
H-capital	0.35 (0.11)	-0.31 (0.15)

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Essay 4*

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Regional Convergence, Prices, and Geography: A Study of the Swedish Regions, 1911-1993.

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Abstract
Do regional per capita incomes converge or diverge, is per capita income growth in nearby locations interdependent of each other, and what are the effects of PPP adjusting income? In this paper we analyse convergence patterns and channels for growth spillovers with an explicit spatial econometric approach using data on Swedish counties spanning the period 1911-1993. We find counties per capita income growth to be strongly related to the growth rate in contiguous counties. There is also evidence of growth spillovers through income and market size in contiguous counties. We find a significant impact of agglomeration, demographic structure, and population growth on counties per capita income growth. However, if we make a regional PPP adjustment of income by way of cost of housing, the growth effects of these variables becomes insignificant. This is because of a systematic dependence between these variables and the cost of housing.

Keywords: Spatial econometrics; Spillovers; Convergence; PPP-adjustment; Demography
JEL codes: C29 O18 R11

* **Acknowledgements:** Financial support from Jacob Wallenberg research foundation to the first author is gratefully acknowledged.

1. Introduction

The convergence in per capita income hypothesis has been vividly discussed in recent macroeconomic literature. Baumol (1986) made an important contribution followed by De Long (1988). This and the breakthrough of endogenous growth models by Romer (1986, 1990) and Lucas (1988) triggered a large number of studies of regional income convergence.[1]

As noted by Temple (1999), convergence studies typically do not allow for interdependent observations, that is, growth in different locations is treated as independent of each other, an assumption, probably not supported by real world data. Some exceptions from the independent observations assumption are Moreno and Trehan (1997), Gustavsson (1997), and Montouri and Rey (1999) that allows for spatial interdependency when studying convergence among countries in the Penn World Tables for the first author, and US states, for the others.[2] Armstrong (1995) and Chattrerji and Dewhurst (1996) use a more explicit spatial treatment. López et al (1999) make use of spatial approaches when studying convergence and dynamics among European regions.

In analysing spillovers, Alfred Marshall (1920) argued that the decision of where to locate industrial activities is affected by three categories of returns to agglomeration. Briefly, he argued for (1), knowledge spillovers that loosely speaking are in the air, (2), forward and backward linkages (today formalised in the new economic geography literature)[3] and, (3), labour market pooling. For the first and second, distance is implicitly involved whereas the size of cities are central for the latter.

In the endogenous growth literature, technological spillovers are present in some models; see, for example, Barro and Sala-i-Martin (1995 Ch 8) for a leader follower model and Aghion (1999) for technology transfer models.

Reasons to believe that knowledge is to some extent locally bounded are put forward as five 'stylised facts' by Dosi (1988), and further developed

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[1] See Durlauf and Quah (1999) for a survey and an organizing framework with respect to econometric approach, Barro and Sala-I-Martin (1995) for a survey and description of models, or Temple (1999) for a more recent survey where various statistical problems are discussed.

[2] Examples of regional convergence studies are seen in Sala-i-Martin (1996), Pekkala (1999) and Kangasharju (1999) for studies on Finnish regions, Persson (1997) for a study on Swedish counties, and Armstrong (1995) for European regions.

[3] See e.g. Krugman, Fujita and Venables (1999).

by Feldman (1994a, 1994b) and Baptista and Swann (1998). Finally, there exists a growing literature that focuses on the spatial dimension of economic growth; some recent examples are Amiti (1998) and Hanson (1998) who focus on the concentration of industrial activities in Europe and the US, respectively. In a recent book by Marjolein (2000) some theoretical modelling (and a brief survey) of knowledge spillovers across space is presented.

In this paper we explore convergence in per capita income and patterns of spatial dependence across the 24 Swedish counties covering the period 1911-1993. The analysis indicates a greater dispersion in growth rates as well as spatial interdependence between periods than cross-sectionally. Dividing the sample into eight periods, regressions indicate convergence in all periods except in the 1920s and the 1980s[4]. For the 1980s convergence is significant when adding conditional variables to the analysis. This is comparable to the lack of convergence among US states in the same time periods[5].

Measuring the speed of convergence in different periods, absolute convergence models indicate a speed of convergence ranging from roughly 0.4 percent annually in the 1920s to 7.8 percent in the 1970s.

In analysing spatial interdependency in regional per capita growth rates, we find robust and significant evidence for spatially autocorrelated growth rates; that is, growth rates in one county are found to be dependent on growth rates in contiguous counties. Econometrically this is modelled as a spatially interdependent error term. The interpretation is that the Swedish counties are exposed to common shocks. That is, if a county experience a positive growth shock such that per capita income growth is higher than predicted by the model, we expect its neighbours to be part of the same shock.

To analyse additional growth spillovers, we append per capita income and market size in contiguous counties to the analysis. These channels are also investigated in a spatial context by Moreno and Trehan (1997), and Montouri and Rey (1999), where the latter only investigate the per capita income channel. In essence, we find evidence for both types of spillovers but, due to collinearity, it is hard to distinguish between them.

The data set collected by Alan Heston and Robert Summers makes a serious attempt to control for differences in price levels across countries using an advanced weighting procedure. The goal is to produce PPP-adjusted incomes. This is to be compared with World Bank data that are

[4] These results are previously reported in Persson, (1997).

[5] See Barro and Sala-i-Martin, (1995).

not PPP-adjusted.[6] In this paper, we compare results using non-PPP-adjusted income versus income PPP-adjusted by controlling for regional differences in the cost of housing[7]. By doing this, we are able to detect and explore interesting features about variables that we think are important determinants for the steady-state income level.

We find demographic variables, which are often not included in convergence studies, to be systematically related to the regional cost of housing. In particular, we find the population share in non-productive age (share of population less than 15, and more than 65 years old) to be negatively related to growth. However, using PPP-adjusted income this relation becomes insignificant.

Maybe most interesting, we find that agglomeration is shown to have a positive effect on growth only when using unadjusted income. This feature may emerge due to an increased cost of housing in agglomerating areas.

Among the control variables, only the net migration rate is found to have a (negative) robust impact on per capita income growth independently whether income is PPP-adjusted or not.

Contributions in this paper include: (I) a thorough investigation of the often ignored spatial dependence showing that spatial interdependence varies more in time than in the cross sectional dimension; (II) we analyse the spatial pattern of growth spillovers through income and market size, allowing for a contemporary common shock structure (to the best of our knowledge not investigated in this way before); (III) by using income with and without adjustment for regional differences in the cost of housing (regional PPP adjustment) we explore and reveal a systematic dependence between demography, agglomeration, and population growth on the regional cost of housing.

The paper is organised as follows. In section 2 we describe the data and perform an exploratory data analysis. In section 3 we provide a formal regression analysis. Concluding remarks are given in section 4.

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[6] See Debray Ray, (1998), "*Development Economics*", for details.

[7] See Persson (1997), for details about the PPP-adjustment procedure.

2. Data and Exploratory Data Analysis

In this section we describe the data and perform an explanatory analysis of the data. We use data on the twenty-four Swedish Counties for the period 1911-1993. The sample period is divided up into eight roughly 10-year periods. Thus, we use a panel data set. We end the sample period in 1993 partly in order to obtain sub periods of roughly equal size. The income concept is real per capita income net of taxable government transfers. There are no official regional price indices for Sweden. However, we make use of cost-of-living adjusted incomes based on Persson (1997). Persson (1997) shows that the main reason to the county differences in price levels is due to county differences in the cost-of-housing. As a result, the cost-of-living adjustment is mainly based on the cost of housing[8].

We first analyse whether there is geographical or spatial dependence between the counties' per capita income growth rates; that is, we analyse whether a county's growth rate of per capita income tend to be correlated with the growth rates of its neighbouring counties[9]. To be more precise, we study the spatial dependence between the growth rate of per capita income (g) and the average growth rate of neighboring counties - the so-called spatial lag ($W \cdot g$). W is a square, block diagonal matrix, with the number of rows and columns in each block equal to the number geographical units. The element w_{ij} reflects the assumed spatial dependence between locations i and j. Thus, the values of the matrix is assumed a priori. In practice, one assumes that spatial dependence declines with distance[10]. We let W to be a first order contiguity matrix, which means that w_{ij} = 1 if county i and j share a common border and $w_{ij} = 0$ otherwise.[11]

In the exploratory analysis we measure spatial dependence using the Moran I statistic[12]. Using the pooled dataset; that is, the cross section of counties observed for the eight sub periods of the sample period 1911-1993, the Moran I statistic is positive, 0,24, and significant (p-value = 0.005[13]). Thus, counties with high (low) growth rates tend to be located

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[8] For a detailed description of the data including the cost-of-living adjustment, see Persson, (1997).

[9] Spatial dependence is sometimes called spatial autocorrelation.

[10] One measure of distance often used is travel time.

[11] The only island in the sample, Gotland, is treated as an isolated observation in the weight matrix W.

[12] Cliff and Ord, (1971, 1973, 1981).

[13] All spatial tests and regressions were obtained using SpaceStat, Anselin (1995). The p-value is based on 2000 permutations. Moreover, if we use unadjusted incomes we also

near counties with high (low) growth rates, more than would be expected due to randomness.

Figure 1 and 2 provide a more detailed picture on spatial dependence. Figure 1 plots the average annual growth rate of per capita income and the average corresponding growth rate of neighbouring counties. In figure 1 and 2 the observations are ordered so that within each time period there are twenty-four observations. Each observation represents one county. One conclusion we draw from Figure 1 is that it appears to be a greater variation in the growth rate over time than over counties. The sample variance of the growth rate of per capita income within and between time periods is 5.1E-05 and 0.00035, respectively. This may be taken as an indication of an integrated economy.

Figure 2 plots the local Moran statistics. It indicates for each location whether it is spatially autocorrelated with its neighbors. Thus, for each observation this statistic gives an indication of the extent of significant spatial clustering of similar values around that observation[14]. We calculate one local Moran statistic for each county and time period. Figure 2 plots both the local Moran statistics and their corresponding z-values. The z-value follows a standard normal distribution. In order to obtain roughly the same amplitude between the local Moran statistic and its z-value, the local Moran statistic is multiplied by a factor of five. Several observations can be made from Figure 2. First, the spatial autocorrelation tends to be non-negative. Second, the degree of spatial autocorrelation varies across time periods. For example, the periods 1911-1921, 1940-1950 and 1980-1993 are characterized by relatively high positive spatial dependency. Third, there appears to be no time trend (upward or downward) in the degree of spatial dependence. Fourth, there is a greater variation in spatial dependence over time than over counties (within a given time period): The sample variance in the local Moran statistic, between and within time periods is 0.35 and 0.06, respectively. Moreover, from figure 1 and 2 we see that for most time periods, except for the 1980s, high growth is associated with a high degree of positive spatial dependence. (The sample correlation between the growth rate of per capita income and the local Moran statistics is 0.71 (p-value=0,00) for the period 1911-1980. However, for the whole sample period the corresponding sample correlation is practically zero, 0,01.) The 1980s is an exception in the sense that despite a

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find a positive and significant spatial interdependence for the growth rate of per capita income.

[14] The average of the local Moran statistics will equal the global Moran I statistic, up to a factor of proportionality.

low average growth rate of per capita income, there is a statistically significant strong positive spatial dependence.

Fig 1. Per capita income growth and its spatial lag.

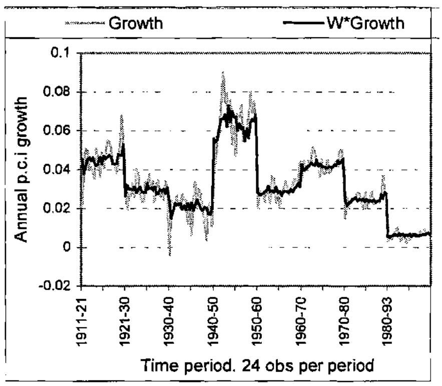
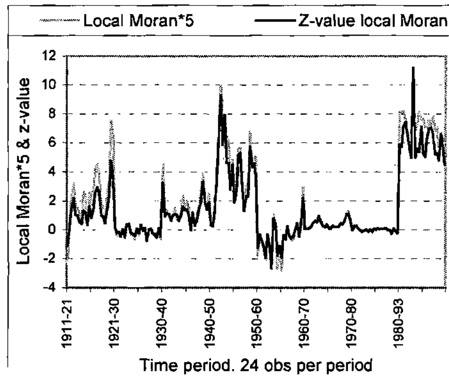


Fig 2. The local Moran statistic.



An alternative way to view the data is to study maps. Figure A1 shows the counties' per capita incomes for 1911, 1960, and 1993. We do not plot growth rates but they tend to be inversely related to per capita income because of strong absolute convergence. Even though we do not present any statistical test there appear to be spatial clustering with respect to per capita income. This is not surprising given that there is spatial clustering with respect to the growth rate of per capita income and there exist absolute convergence. Perhaps the most interesting thing that comes out of these figures is that rankings change when we allow for cost of living adjustment. For example, comparing cost of living adjusted income with unadjusted income in 1993, we can see that the ranking, with respect to per capita income, changes for the upper north of Sweden. When differences in cost of living are accounted for the upper north belong to the class of counties with the highest per capita income.

3. Regression analysis

3.1. Absolute convergence

In this section we report results from absolute convergence regressions. We contrast the results from the standard absolute convergence regressions that do not allow for spatial dependence with the results from absolute convergence regressions that do allow for such dependence. In testing for absolute convergence across counties we estimate the following regression equation:

$$(1/T)\ln(y_{i,t-T} / y_{i,t}) = \alpha_t + \beta_t \ln(y_{i,t}) + \varepsilon_{i,t} \qquad (1)$$

where t = 1911, 1921, 1930, 1940, 1950, 1960, 1970, and 1980. T is the length of the sample period, y_{it} is county i's per capita income at time t, ε is the error term, α is the intercept, and β is the convergence parameter. A negative estimate of β indicates absolute convergence.

The results from absolute convergence regressions that do not account for spatial dependence are reported in columns 1 and 4 of *Table 1*. Column 1 report the results based on incomes that are adjusted for regional differences in cost of living and column 4 reports results based on income that are not adjusted for regional differences in cost of living. Results displayed in column 1 indicate that convergence occurs in most 10-year periods. Only in the 1920s and 1980s is there lack of convergence. The 1920s was a period with falling relative prices of agricultural products that hurt the relatively poor agricultural counties most. Column 4 gives the same qualitative results. A quantitative difference is, however, that the estimated betas in column 1 tend to be higher in absolute values, which indicates a higher estimated speed of convergence.

Introducing spatial effects and the weight matrix

The exploratory data analysis indicated spatial autocorrelation. We allow for spatial interdependency in the absolute convergence regressions either by including neighbours' growth rates as an explanatory variable or by a spatially interdependent error term (common shocks).

In the regressions we make use of a row standardised contiguity matrix W. Row standardising means that each row sums to one, which implies that the coefficient of spatial dependence will be bounded from above by one. Thus, it is possible to interpret the spillover parameter in economic terms.

In addition to the contiguity matrix, we have also tried alternative weight matrices where $w_{ij} = d_{ij}^{-k}$, $k>0$, and d_{ij} is an estimate of the travel time by car (1996) from location i to j. Setting $k = 2$ gave results similar to those produced by the contiguity matrix. Finally, we tried with GDP weighting such that w_{ij} is increasing in GDP_j and decreasing in d_{ij}. The logic behind this weighting is that, for a given distance between location i and j, county i should be more affected of county j the bigger GDP is in j. This specification did, however, not improve the performance of the weight matrix.

Estimation

The implication of not correcting for non-independent observations is an omitted variable bias. On the other hand, introducing a spatial lagged dependent variable as an explanatory variable is similar to the endogenous variable problem and OLS is no longer a consistent estimator. If the spatial interdependency on the other hand is in the error term, this is like a non-spherical error and OLS yields unbiased parameter estimates but biased parameter variance.

The most commonly used way to handle spatial effects in practise is by estimation of the spatial lag, or the spatial error model. These are specified in equation 2.1 and 2.2.[15]

The Jarque-Beras test rejects normality in the residuals at the one percent significance level for all models. Therefore we use robust estimators when estimating the models. Further, likelihood ratio tests indicate groupwise heteroscedasticity with respect to time, significant at the one percent level for all models.

For the spatial error models we use a GMM estimator corrected for groupwise heteroscedasticity with respect to time[16]. For the spatial lag models we use 2SLS corrected for groupwise heteroscedasticity with respect to time[17].

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[15] The connection between these models is easy to show; this relationship and a survey of spatial models is given in Anselin, (1988).

[16] Kelejian and Prucha, (1999)

[17] Typically IV-based (robust) spatial estimators use spatial lagged transformations of independent variables as instruments.

Table 1: Absolute convergence models.
Dependent variable, mean annual growth of per capita income.

	PPP-adjusted income			Unadjusted income		
Model Estimator	**OLS**	**Spatial lag[A] 2SLS-G[B]**	**Spatial error GMM-G**	**OLS**	**Spatial lag[A] 2SLS-G**	**Spatial error GMM-G**
Variable	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)
y(1911)	-0.019 (-6.66)	-0.019 (-5.53)	-0.019 (-5.02)	-0.017 (-6.31)	-0.016 (-5.13)	-0.017 (-4.65)
y(1921)	-0.004 (-1.20)	-0.004 (-1.14)	-0.004 (-0.94)	-0.004 (-1.13)	-0.004 (-1.09)	-0.003 (-0.83)
y(1930)	-0.020 (-5.94)	-0.021 (-4.43)	-0.023 (-5.07)	-0.022 (-6.67)	-0.020 (-4.78)	-0.025 (-5.59)
y(1940)	-0.048 (-11.49)	-0.047 (-9.38)	-0.047 (-9.31)	-0.045 (-11.45)	-0.043 (-9.72)	-0.045 (-9.40)
y(1950)	-0.027 (-3.72)	-0.027 (-4.51)	-0.025 (-3.70)	-0.018 (-2.66)	-0.024 (-4.62)	-0.017 (-3.24)
y(1960)	-0.038 (-4.18)	-0.040 (-10.76)	-0.037 (-11.26)	-0.023 (-2.92)	-0.032 (-8.56)	-0.024 (-6.79)
y(1970)	-0.056 (-3.93)	-0.057 (-13.17)	-0.054 (-11.28)	-0.045 (-4.40)	-0.036 (-9.34)	-0.042 (-12.37)
y(1980)	-0.013 (-0.44)	-0.014 (-1.32)	-0.010 (-1.00)	0.001 (0.07)	-0.015 (-2.83)	0.001 (0.28)
W^r*e			0.2350			0.340
W^r*g		0.0997 (3.19)			0.1086 (2.98)	
R^2. (Sq. Corr)	0.940	0.942 (0.946)	0.943 (0.939)	0.933	0.942 (0.940)	0.936 (0.932)
p-value. LM-test error (lag) dependence[C]	0.002 (0.077)			0.000 (0.036)		

Notes for *Table 1*: g = mean annual growth rate in per capita income (the dependent variable).
Weight matrix W^r = Row standardised first order contiguity matrix.
192 observations in each model.
Period dummies and a constant included in all models.
[A] Instruments: Spatial lagged; p.c.i, GDP, share young, share old, agglomeration, population growth and net migration.
[B] "G" indicates that the regression is corrected for groupwise heteroscedasticity with respect to time.
[C] For GMM models the error parameter is considered to be a nuisance parameter, in that it helps estimation of other parameters. No t-value is available, therefore we present a separate test for type of spatial dependence.

Estimation results

In *Table 1*, we present results from absolute convergence models that allow for spatial effects. They are specified as follows:

The spatial lag model:

$$(1/\mathrm{T})\ln(\mathrm{y}_{\mathrm{i,t\text{-}T}}/\mathrm{y}_{\mathrm{i,t}}) = \alpha_t + \beta_t \ln(y_{i,t}) + \rho W_t^r (1/\mathrm{T})\ln(\mathrm{y}_{\mathrm{i,t\text{-}Y}}/\mathrm{y}_{\mathrm{i,t}}) + \upsilon_{i,t} \tag{2.1}$$

The spatial error model:

$$(1/\mathrm{T})\ln(\mathrm{y}_{\mathrm{i,t\text{-}T}}/\mathrm{y}_{\mathrm{i,t}}) = \alpha_t + \beta_t \ln(y_{i,t}) + \varepsilon_{i,t} \;;\; \varepsilon_{i,t} = \lambda W_t^r \varepsilon_{i,t} + \upsilon_{i,t} \tag{2.2}$$

where t = 1911, 1921, 1930, 1940, 1950, 1960, 1970, and 1980. T is the length of the sample period, y_{it} is county i's real per capita income at time t, α is the intercept, and β is the convergence parameter, W^r is a row standardised first order contiguity matrix. Finally, ρ and λ are pooled parameters (over time periods) that measure the degree of spatial lag and error dependency, respectively, ε is the spatially autocorrelated error term, and υ is white noise.

Tests reported in *Table 1* indicate the presence of significant spatial dependency, independently of choice of model specification (spatial lag or error). Comparing these, the spatial error specification model performs slightly better.

The interpretation of an estimated spatial lag parameter of 0.0997 is as follows; if the average growth rate of per capita income in neighbouring locations increases by one percentage point we expect the per capita income to grow by 0.0997 percentage points. For the spatial error model, the corresponding interpretation is as follows; for a given average (growth) shock to neighbours of one unit, we are expected to be hit by a positive shock of λ units.[18] The estimated λs are found to be in the neighbourhood of 0.24 (0.34) using PPP-adjusted (unadjusted) income.

A common feature for all models (conditional and unconditional) is that for regressions based on *unadjusted income* the parameter measuring spatial dependence is larger (and more significant). When we apply Moran's I statistic on the cost of housing index we find a positive spatial autocorrelation (p=0.000). Therefore, adjusting income for regional cost of housing may pick up some spatial effects.

Spatial dependence, to some extent, equalizes regional growth rates. Therefore, we would expect the explicit introduction of spatial dependence in the regression to pick up some convergence, bringing the speed of convergence parameter towards zero. Comparing the estimated β-parameter

[18] This straightforward interpretation is only possible for row-standardised weight matrices.

for the three different absolute convergence models in *Table 1* reveals only small changes in the betas when spatial dependence is allowed for. Moreover, the overall fit of the models is high with an indicative R^2 in the neighbourhood of 0.93-0.94.[19]

3.2. Conditional convergence

In this section, we estimate conditional convergence regressions that among other things, allows us to investigate some specific sources of spillovers. The theoretical framework is based on the neoclassical growth model (e.g. Solow, 1956) and, analogous to Durlauf and Quah (1999) who use a Cobb-Douglas specification for different types of physical capital, we use Cobb-Douglas specification for different types of human capital. We assume that different age groups represent different types of human capital[20]. We allow people of different age cohorts to differ in productivity. The population is divided into three age categories where n_1 and n_3 refers to shares of people young (< 15 years old) and old (< 65 years old) respectively, and n_2 is the reference group (20-65 years old). By these assumptions, income per person in efficiency units is given by:

$$\hat{y} = A\hat{k}^{\alpha} n_1^{\gamma_1} n_2^{\gamma_2} n_3^{1-\alpha-\gamma_1-\gamma_2} \qquad ; \hat{k} = K / e^{xt} N,\ n_i = N_i / N;\ i = 1,2,3. \tag{3}$$

where $\hat{y}$ is income per capita in efficiency units, K is the capital stock, N is total population, x is the exogenous rate of technical progress, and A is the level of technology. It is straightforward to show that this production function yields the following conditional convergence regression model:

$$(1/\mathrm{T})\ln(\mathrm{y}_{i,t-T} / \mathrm{y}_{i,t}) = \alpha_i + \beta_t \ln(y_{i,t}) + c_1 \ln(\tilde{n}_1) + c_2 \ln(\tilde{n}_3) + \varepsilon_{i,t} \tag{4}$$

In equation 4, $\tilde{n}_k = n_k/n_2 = N_k/N_2$, where $k = 1,3$. In the empirical analysis we append additional control variables to the model and allow betas to vary with respect to time. For other variables we apply fixed coefficients.[21]

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[19] In models with non-spherical errors, R^2 values are only indicative. As a result, an alternative measure of fit (squared correlation) is presented as well.

[20] For details, see Persson, (1999), and Lindh and Malmberg, (1999).

[21] Likelihood ratio tests on models presented here indicate that the control variables may not fulfil the stability criterion. On the other hand, Schwartz information criteria slightly favour the restricted models. To be careful, we have estimated full space-time SUR models resulting in a large number of parameters to evaluate and little new insights all pointing to the restricted model to be a proper specification.

We expect the share of young $\tilde{n}_1$, and old $\tilde{n}_3$, people to have a dampening effect on the growth rate of per capita income since this implies a smaller part of the population in production.[22]

The new economic geography literature infers that as trade costs decline, agglomeration forces is strengthened[23]. For transportation costs above zero and below the so-called sustain point, in the agglomerating areas, the real wage will be higher than in the periphery.[24] We use the population density as a proxy for the level of agglomeration in a county and expect this variable to have a positive effect on growth. Finally, we introduce migration rates, population growth, and explicit channels for growth spillovers via neighbouring counties markets size and per capita income.

3.2.1. Results

Demography

Conditional convergence results are presented in *Table 2*.

Regressions using income adjusted for cost of housing reveals a negative and not significant effect of the demography variables on growth.[25] On the other hand, using unadjusted income data both the share of young and old people becomes negatively significant. The logic behind these results may go as follows. Inspection of the correlation between the cost of housing index and demography reveals a negative significant correlation (corr = -0.13 p-value 0.08 for young, and corr = -0.29 p-value 0.00 for share of old).[26] This means that in particular old people tend to live in regions with low cost of housing. Hence adjusting income for the cost of housing may pick up some demographic effects as well. This may just simply be that people of productive age tend to move to the cities to get jobs (and maybe move to more rural regions as they grow old).

[22] Following Barro and Sala-i-Martin (1995, p 438) it is also possible that a large share of young people reduces the time spent in production for people with children (a part of the reference group) since parents may substitute time from production to household activities.

[23] See e.g. Fujita *et al,* (1999)

[24] For transportation costs, close to zero convergence instead of divergence in real wages is possible as trade costs decline.

[25] We use shares and not log of shares in the regressions.

[26] Running separate regressions explaining the share of young and old people, respectively, using the cost of housing, a constant, and period dummies, yields a negative and insignificant (significant) partial impact of the cost of housing on the share of young (old) people. The coefficients are –0.22 (-0.84) and the t-values are –1.24 (-11.99), respectively.

Table 2: Conditional convergence models.

Dependent variable, mean annual growth of per capita income.

	PPP-adjusted income			Unadjusted income		
Model **Estimator**	**Mod c1** **GMM-G**[A]	**Mod c2** **GMM-G**	**Mod c3** **GMM-G**	**Mod c1** **GMM-G**	**Mod c2** **GMM-G**	**Mod c3** **GMM-G**
Variable	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)
y(1911)	-0.020 (-4.77)	-0.017 (-4.26)	-0.017 (-4.37)	-0.218 (-5.35)	-0.019 (-4.97)	-0.020 (-5.08)
y(1921)	-0.005 (-1.11)	-3.0E-4 (0.06)	-9.9E-05 (-0.02)	-0.009 (-2.33)	-0.004 (-0.98)	-0.004 (-1.03)
y(1930)	-0.024 (-5.00)	-0.019 (-3.83)	-0.020 (-3.87)	-0.032 (-6.76)	-0.027 (-5.34)	-0.027 (-5.36)
y(1940)	-0.048 (-9.15)	-0.038 (-5.92)	-0.038 (-5.96)	-0.052 (-10.79)	-0.043 (-7.28)	-0.043 (-7.27)
y(1950)	-0.025 (-3.47)	-0.011 (-1.32)	-0.011 (-1.37)	-0.027 (-4.62)	-0.015 (-2.04)	-0.015 (-2.06)
y(1960)	-0.036 (-8.62)	-0.020 (-2.60)	-0.020 (-2.64)	-0.035 (-8.11)	-0.022 (-3.16)	-0.022 (-3.15)
y(1970)	-0.050 (-8.23)	-0.072 (-8.03)	-0.071 (-7.96)	-0.059 (-10.75)	-0.067 (-10.01)	-0.067 (-10.03)
y(1980)	-0.003 (-0.24)	-0.023 (-2.01)	-0.022 (-1.87)	-0.026 (-2.78)	-0.026 (-3.040)	-0.025 (-2.97)
W^r*e	0.212	0.233	0.2511	0.3443	0.3241	0.3214
W^r*y		8.5E-04 (3.00)			8.0E-04 (2.94)	
W^r*ln GDP			1.6E-04 (2.78)			1.6E-04 (2.76)
Share age < 15 years	-0.0102 (-1.23)	-0.0119 (1.37)	-0.0128 (-1.48)	-0.0227 (-2.55)	-0.0194 (-2.21)	-0.0202 (-2.30)
Share age > 65 years	-0.0033 (-0.40)	-0.0055 (-0.68)	-0.0055 (-0.68)	-0.0272 (-2.73)	-0.0259 (-2.92)	-0.0259 (-2.89)
Population density (Agglomeration)	-1.1E-05 (-1.97)	-4.3E-07 (-0.07)	-9.6E-07 (-0.16)	1.8E-05 (2.36)	2.6E-05 (3.39)	2.5E-05 (3.35)
Net migration		-0.6402 (-2.86)	-0.6264 (-2.80)		-0.4989 (-2.18)	-0.4968 (-2.17)
Pop growth		0.0387 (0.89)	0.0390 (0.89)		0.1218 (2.96)	0.1218 (2.95)
R^2 (Sq.corr)	0.942 (0.940)	0.945 (0.940)	0.946 (0.940)	0.941 (0.935)	0.940 (0.937)	0.942 (0.938)
p-val. LM-test. Spatial, error (lag) dependence	0.002 (0.049)	0.048 (0.291)	0.057 (0.438)	0.002 (0.037)	0.006 (0.892)	0.008 (0.345)

Notes for *Table 2*: y = Log of initial per capita income. W^r = Row standardised contiguity matrix. 192 observations in each model. Period dummies and a constant included in all models.

[A] "G" indicates correction for groupwise herteroscedasticity with respect to time.

Using model c2 in *Table 2* and unadjusted income, the partial effect of a one percentage point increase in the proportion of people less then 15 years of age (more than 65 years) compared to those 20-65 years reduces growth by 0.0194 percentage points. A more detailed study of the lifecycle migration patterns and regional growth is left for future research.

Agglomeration

Using PPP-adjusted income, the estimated impact of agglomeration on growth is negative and mostly insignificant. On the other hand, using unadjusted income, we find a positive and significant effect of agglomeration on growth in per capita income. A possible explanation for these seemingly contradictory results is that agglomeration may not only increase wages but also increase demand and the price of land, and by this the cost of housing as well. This is not surprisingly since the cost of housing is closely related to the price of land.

That agglomeration increases the cost of housing theory is supported when regressing agglomeration on the cost of housing index. The coefficient estimating the impact of agglomeration on the cost of housing index is found to be 0.0002 with a t-value of (4.88).[27] As a consequence, if we omit the cost of housing when comparing real income, agglomerating areas will tend to have higher income and growth. On the other hand, the cost of housing will rise in expanding regions, apparently to such an extent that when the cost of living is controlled for, the positive income and growth effect of agglomeration is wiped out.

The estimated growth effect of an increase in the population density by 10 units is found to be in the range of 0.018-0.026 percentage points depending on what specification we use.

Population growth and migration

All variables except population growth and net migration rates are taken as initial values in each period. Thus, there is no severe endogeniety problem. The migration rate and population growth are, however, measured as averages over each time period and we use IV techniques when introducing these variables.[28] Instruments for the net migration rate are time-wise

[27] Period dummies included. The correlation matrix also indicates a positive correlation between these variables.

[28] Net migration rate is calculated as $1/T * (\sum_{t=1}^{T} \text{inflow - outflow})/ (\text{pop})_t$ for each region.

Population growth net of migration is calculated as $\{\ln[(\text{pop})_{t+T} - (\text{net migr})_{t+T}] - \ln(\text{pop})_t\}/T$.

lagged values of migration, initial per capita income for each time period, demographic variables, and period dummies.[29] For population growth (net of migration) we use time-wise lagged population growth, initial per capita income, demographic variables, and period dummies as instruments.[30]

Referring to the Solow model it is easy to motivate the introduction of the population growth variable, with an expected negative impact on growth in per capita income. In practice, things are not that simple. Population growth (net of migration) consists of the birth rate and the death rate. When we allow for differences in productivity with respect to age, we can easily imagine at least three cases: Case 1, an exogenous increase in the death rate of young and old people will, ceteris paribus, increase growth; Case 2, an increase of the death rate of people of productive age dampens growth; Case 3, a rather similar change in mortality over cohorts implies some ambiguity in the expected effect on growth.

The partial effect of population growth, on growth in per capita income, indicates a positive insignificant (significant) effect using PPP-adjusted (unadjusted) income. This result contrasts somewhat to Barro and Sala-i-Martin (1995 ch 12) who find a negative insignificant/significant[31] impact of population growth on per capita income growth, using cross-country data by Barro and Lee (1994).

In quantitative terms, we find the partial effect of a one-percentage point increase in population growth to imply an expected increase in per capita income growth of 0.04 (0.12) percentage units, using adjusted, (unadjusted income). The parametric difference using raw and PPP-adjusted income may work through a negative correlation between cost of housing and population growth (corr -0.18, p-value 0.01).[32]

Analysing the partial effect of migration, we find a negative impact of migration rates on per capita income growth. This is consistent with diminishing returns to labour. A strong positive correlation between per capita income and net migration indicates that net migration goes from poor to rich counties, a finding supported by regressing initial per capita income on net migration.[33] The conclusion is that migration tends to

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[29] IV regression R^2 is 0.59

[30] IV regression R^2 is 0.45

[31] Significance is dependent on which controls they include in the regression.

[32] Regressing the cost of living on population growth, a constant, and period dummies yields a negative estimate of the cost of living parameter: coefficient = -0.04 and t-value = -3.05.

[33] Regressing initial per capita income on migration, a constant, and period dummies, yields a positive estimate for the initial income variable: coefficient = 0.011 and t-value = 8.90.

promote convergence; therefore including this variable should reduce the estimated value of the speed of convergence. In regressions performed the drop in estimated betas is only marginal, suggesting that migration does not account for a large part of β-convergence[34].

The estimated coefficients suggest that a 0.1 percentage point increase of net migration as a share of total population reduces growth in "receiving" regions by roughly 0.06 (0.05) percentage points, using PPP adjusted (unadjusted) income.

Substantial spatial spillovers

When introducing alternative channels for spillovers, the spatial lag specification cease to produce a significant spatial lag, while the spatial error term coefficient is almost unaffected. In *Table 2*, we can see that for a county, a shock of a weighted average size of one unit in contiguous counties implies an expected shock of roughly 0.22 (0.34) units, using PPP-adjusted (unadjusted) income: a growth shock fades out as it is propagated out over counties. This is similar to results from the estimated spatial unconditional regression models presented in *Table 1*.

From an economic perspective, it is interesting to perform a deeper analysis of possible routes for growth spillovers. One candidate is per capita income in contiguous counties. Income spillovers may promote growth through demand effects from rich counties,[35] or through human capital spillovers (capitalised in high per capita income) that facilitate the absorption of new technologies (Cohen, 1989). With this dataset we cannot discriminate among these hypothesis.

In *Table 2* and model c2, the log of initial per capita income at contiguous counties is introduced as a regressor. We find evidence for positive growth effects through income levels in surrounding counties.

On the basis of the estimates, we would expect a weighted increase in income of 10 percent in contiguous counties to boost growth by 0.008 percentage units. This is consistent with Moreno and Trehan (1997) (but smaller in magnitude) in their spatial cross-country analysis. Rey and Montourin (1999), however, do not find any significant growth boosting spillovers through per capita income when analysing US states.

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[34] These results are consistent with Barro and Sala-i-Martin (1995 ch 11.8), and Persson, (1997).

[35] Demand effects may have a bias towards firms located relatively close. In a global sense, this is highlighted by the commonly estimated gravity equations; see Frankel and Romer (1999) for a recent study.

Location close to a large market, measured as regional GDP, may be good for growth if trade and expenditures have a tendency to decrease with respect to distance. In model c3, *Table 2*, we introduce regional GDP in surrounding counties to the analysis. We find evidence of significant growth spillovers through neighbouring counties GDP.

For a county, a weighted average increase of 10 percent in GDP in surrounding counties implies an expected increase in per capita income growth of roughly 0.0016 percentage points.[36] However, spatially weighted market size and per capita income are relatively highly correlated (corr 0.80) and if we use them together, neither of them turns out to be significant. Other variables, however, are not substantially affected. The implication from an econometric perspective is that it is difficult to distinguish between growth-boosting spillovers through income or market size[37].

Robustness of results

In order to capture substantial spillovers, we performed the same analysis with the contiguity matrix which was not row standardised. This did not alter the results. Nor do the spillover results depend critically on the inclusion/ exclusion of other variables. Introduction of the net migration rate and population growth (net of migration) does not substantially affect the partial effect of demography (or other) variables on growth in per capita income.

One striking feature is that even though we add additional ways for spatial spillovers, or other control variables, the parameter value and significance of the spatial error term parameter measuring common shocks is basically unchanged. This gives us an indication of how difficult it is to find variables that catch all kinds of spillovers. At last, focusing on the speed of convergence, this is very stable when introducing additional variables, suggesting that β-convergence does not depend critically on the mechanisms analysed here.

[36] Moreno and Trehan (1997) also find a positive growth effect through GDP in contiguous countries: In their study, the GDP spillover was more robust than spillovers through the level of per capita income. They do not, however, present a deeper analysis of collinearity.

[37] A possible way around this econometric 'problem' is to construct an interaction variable ($y_{it}*Y_{it}$), but this does not deepen our understanding of spillovers.

4. Conclusions

In this paper, we analyse growth and convergence in per capita income (β-convergence) across Swedish counties from a spatial econometric perspective. In the analysis, we use data spanning the period 1911 to 1993.

We studies a set of variables and how the may affect growth in per capita income. These variables are demography, migration, population growth, the level of agglomeration, and growth spillovers. Spillovers may work through (1), per capita income and (2), regional GDP in contiguous counties, or, (3) via a general interdependency working through a spatially interdependent error term, (common shocks).

By using income data adjusted as well as unadjusted for regional differences in cost of housing in combination with spatial techniques, we gain several insights.

The estimated speed of convergence is ranging from 0.4 percent per annum in the 1920s to 7.4 percent in the 1970s (using PPP-adjusted income and absolute convergence models). To be more precise, we generally find absolute convergence in all periods investigated, though this is not significant in the periods 1921-30 and 1980-93. If we add conditioning variables the last period gives significant convergence while the period 1921-1930 continues to show a lack of convergence. This is similar to findings on convergence among the US states. One possible explanation for the lack of convergence in the 1920s is the decrease in world market prices in agriculture experienced at that time. This affected the already poor agricultural regions most[38]. The similarity in convergence among Swedish counties and US states indicates common international convergence patterns, and that the speed of convergence is not dependent on the size of the geographical units observed.

Appending conditional and growth spillover variables to the analysis does not substantially affect the estimated speed of convergence, indicating a strong robustness in the convergence behaviour.

Comparing growth rates, cross-sectionally and time-wise, reveals a greater dispersion of growth rates in the time dimension compared to the cross-sectional dimension (for a given point in time), indicating relatively homogenous growth rates across counties.

Econometric analysis gives robust evidence for a spatial interdependency in the error term. The interpretation is that counties are exposed to common

[38] See, Barro and Sala-i-Martin, (1995), and Persson, (1997).

growth shocks that fade out as they propagate across counties. The estimated magnitude of spatial error dependence is roughly 0.37 (0.25) using unadjusted (PPP-adjusted income). This means that for an average growth shock of one unit in contiguous counties, we expect a growth shock of 0.37 (0.25) units.

Moran's I-statistic for spatial autocorrelation reveals a significant spatial autocorrelation in the cost of housing. Therefore PPP adjustment of income may pick up some spatial growth interdependence. This may explain why PPP adjustment of income lowers the estimated spatial interdependency in counties growth rates.

Explorative data analysis reveals a generally procyclical pattern in spatial growth interdependence in the sense that high growth is associated with high spatial dependency. An exception, however, is the period after 1980 where we have high levels of spatial interdependency despite of low growth rates in per capita income. We do not, however, find any clear tendency for an increasing spatial interdependency over time

Conditioning on a common shock structure (a spatially interdependent error term), we expand the set of possible spatial growth spillovers with initial per capita income and GDP in contiguous counties. These are shown to generate positive growth spillovers. Due to collinearity between regional GDP and per capita income in contiguous counties, we are not able to fully distinguish between income and market size effects.

Introducing conditional variables, we explore factors important for the steady-state level of income. We augment the production function such that it captures *demographic effects* by allowing people from different cohorts to differ in productivity. We find that a large fraction of old and/or young people (more than 65 years, less than 15 years old) to have a dampening effect on growth in per capita income.

Furthermore, we find evidence for a dependence on where to settle down with age. In particular, we find that the share of old, and to a lesser extent the share of young people, to be negatively correlated with the regional cost of housing. The implication is that PPP adjusting income picks up some demographic effects, reducing the estimated effect and significance of demography on growth when using PPP-adjusted income.

An issue related to the stock variable demography is the flow variable, *population growth*. We find a non-significant (positive significant) partial impact of population growth on growth in per capita income using PPP-adjusted (unadjusted) income. This discrepancy may be driven by a detected, negative correlation between the cost of housing and population growth. This indicates that the decision to have children may be affected by economic factors such as the cost of housing.[39] Barro and Sala-i-Martin (1995), however, find a negative (insignificant) partial correlation between growth in income and population growth.

For *net migration,* we find that migration goes from initially poor to rich counties, dampening growth in "receiving" counties. This is consistent with decreasing return to labour.

Agglomeration, an issue vividly debated and a key issue in the new economic geography, is here proxied with population/km^2. The working hypothesis is that a high level of agglomeration will boost growth since agglomeration is a reinforcing mechanism that increases wages in agglomerating areas.

Indeed, we find evidence for positive growth effects of agglomeration. However, this effect vanishes if we use PPP-adjusted data. A plausible explanation is that the cost of housing increases in agglomerating areas at such a rate that the growth-boosting effect of agglomeration is wiped out by the rise in the cost of housing. This is not surprising since agglomeration raises demand (and the price) of the fixed factor land and that the cost of housing is closely related to the price of land.

In this paper we have among other things highlighted that when measuring income and growth we may end up with very different conclusions whether data are PPP-adjusted or not. We do not want to take a stand for one approach in favour of the other; instead they can be used as complements, and used carefully they can deepening insights when analysing economic growth and factors related to economic growth.

[39] It is also possible to argue for the dependence to go the other way around. That is, given you have decided not to have many children, the alternative cost to live in a region with a high cost of living may be lower. That is to say that the regional cost of living works as a separation mechanism.

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Appendix

Table A1. Correlation matrix.

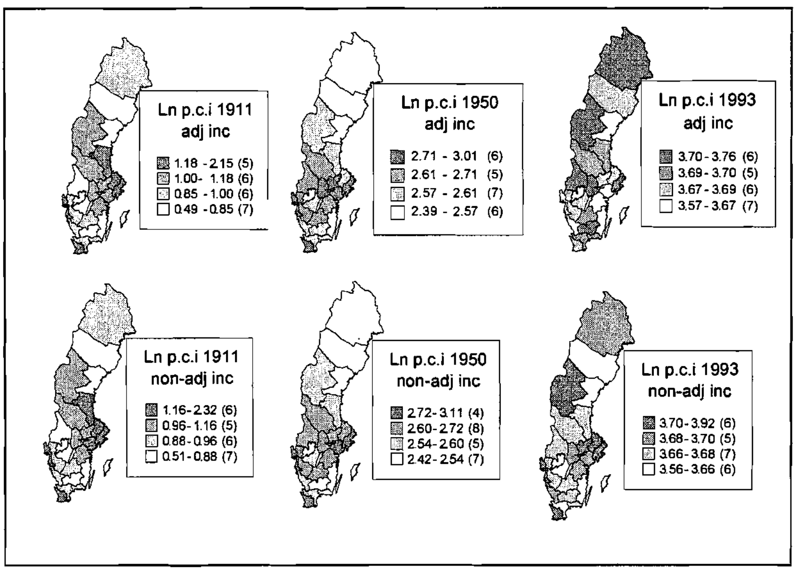
Corr (p-value)	Cost-index	Growth	Growth*	Y	Y*	Share Young	Share Old	Dens (Aggl)	migr*	migr	Popg*	Popg	Wg	Wg*
Index	1.00													
Growth	-0.13 (0.06)	1.00												
Growth*	-0.15 (0.04)	0.99 (0.00)	1.00											
Y	0.21 (0.00)	-0.49 (0.00)	-0.49 (0.00)	1.00										
Y*	0.25 (0.00)	-0.50 (0.00)	-0.50 (0.00)	1.00 (0.00)	1.00									
Share young	-0.13 (0.08)	0.18 (0.01)	0.18 (0.02)	-0.79 (0.00)	-0.79 (0.00)	1.00								
Share old	-0.29 (0.00)	-0.46 (0.00)	-0.46 (0.00)	0.65 (0.00)	0.63 (0.00)	-0.43 (0.00)	1.00							
Pop-density	0.35 (0.00)	-0.23 (0.00)	-0.21 (0.00)	0.27 (0.00)	0.30 (0.00)	-0.31 (0.00)	-0.04 (0.59)	1.00						
Migr*	0.37 (0.00)	-0.31 (0.00)	-0.29 (0.00)	0.56 (0.00)	0.58 (0.00)	-0.64 (0.00)	0.22 (0.00)	0.55 (0.00)	1.00					
Migr	0.36 (0.00)	-0.30 (0.00)	-0.28 (0.00)	0.56 (0.00)	0.58 (0.00)	-0.64 (0.00)	0.22 (0.00)	0.53 (0.00)	0.99 (0.00)	1.00				
Popgr*	-0.18 (0.01)	0.19 (0.01)	0.21 (0.00)	0.01 (0.85)	0.00 (0.96)	-0.15 (0.04)	0.05 (0.48)	-0.22 (0.00)	-0.09 (0.23)	-0.08 (0.28)	1.00			
Popgr	-0.18 (0.01)	0.21 (0.00)	0.22 (0.00)	0.00 (0.97)	-0.01 (0.86)	-0.14 (0.06)	0.04 (0.58)	-0.26 (0.00)	-0.10 (0.18)	-0.09 (0.23)	1.00 (0.00)	1.00		
$W^r g$	0.07 (0.36)	0.83 (0.00)	0.82 (0.00)	-0.42 (0.00)	-0.41 (0.00)	0.13 (0.00)	-0.56 (0.00)	-0.06 (0.37)	-0.12 (0.09)	-0.12 (0.10)	0.01 (0.89)	0.02 (0.74)	1.00	
$W^r g$*	0.06 (0.38)	0.83 (0.00)	0.83 (0.009	-0.42 (0.00)	-0.41 (0.00)	0.13 (0.069	-0.55 (0.00)	-0.05 (0.45)	-0.12 (0.11)	-0.11 (0.12)	0.02 (0.81)	0.03 (0.67)	1.00 (0.00)	1.00
$W^r y$	0.18 (0.01)	-0.40 (0.00)	-0.41 (0.00)	0.86 (0.00)	0.86 (0.00)	-0.68 (0.00)	0.56 (0.00)	0.19 (0.01)	0.44 (0.00)	0.43 (0.00)	-0.07 (0.36)	-0.08 (0.27)	-0.23 (0.00)	-0.23 (0.00)
$W^r y$*	0.18 (0.01)	-0.40 (0.00)	-0.41 (0.00)	0.85 (0.00)	0.86 (0.00)	-0.68 (0.00)	0.56 (0.00)	0.19 (0.00)	0.44 (0.00)	0.43 (0.00)	-0.07 (0.36)	-0.08 (0.27)	-0.23 (0.00)	-0.23 (0.00)
$W^r gdp$	0.10 (0.15)	-0.47 (0.00)	-0.48 (0.00)	0.78 (0.00)	0.78 (0.00)	-0.53 (0.00)	0.68 (0.00)	0.13 (0.08)	0.39 (0.00)	0.39 (0.00)	0.07 (0.32)	0.06 (0.43)	-0.41 (0.00)	-0.41 (0.00)
$W^r gdp$*	0.11 (0.00)	-0.46 (0.00)	-0.46 (0.00)	0.76 (0.00)	0.76 (0.00)	-0.51 (0.00)	0.66 (0.00)	0.12 (0.09)	0.38 (0.00)	0.38 (0.00)	0.09 (0.21)	0.08 (0.29)	-0.41 (0.00)	-0.41 (0.00)

* Based on PPP-adjusted income.

Table A1. Continued.

Corr (p-value)	Wy	Wy*	Wgdp	Wgdp*
Wy	1.00			
Wy*	1.00 (0.00)	1.00		
Wgdp	0.82 (0.00)	0.82 (0.00)	1.00	
Wgdp*	0.80 (0.00)	0.80 (0.00)	1.00 (0.00)	1.00

Fig A1. The log of real per capita income.



Essay 5*

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* Co-authored with Jonas Nordström (Umeå University). Published in: FIEF Working Paper Series: 150. Forthcoming in, Tourism Economics, 2001.

The Impact of Seasonal Unit Roots and Vector ARMA modelling on Forecasting Monthly Tourism Flows*

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Abstract

The effect of imposing different numbers of unit roots on forecasting accuracy is examined using univariate ARMA models. Too see whether additional information improves forecasting accuracy and increases the informative forecast horizon, we crossrelate the time series for inbound tourism in Sweden for different visitor categories and estimate vector ARMA models. The mean-squared forecast error for different filters indicates that models in which unit roots are imposed at all frequencies have the smallest forecast errors. The results from the vector ARMA models with all roots imposed indicate that the informative forecast horizon is greater than for the univarite models. Out-of-sample evaluations indicate, however, that the univariate modelling approach may be preferable.

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* We thank Kurt Brännäs, Jörgen Hellström, Xavier de Luna, and Lars-Erik Öller for helpful comments. Financial support from the Swedish Council for Research in the Humanities and Social Sciences and the Jakob Wallenberg Research Foundation is gratefully acknowledged.

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1 Introduction

The perishable nature of tourism products and the many capacity-related decisions that have to be made well in advance make accurate forecasting of the demand for tourism particularly important. This implies that even small improvements in forecasting the demand for tourism are very valuable. In a survey of tourism demand forecasting, Witt and Witt (1995) pointed out that econometric forecasts did not rank very high in terms of accuracy. In addition, Garcia-Ferrer and Queralt (1997) found the contributions of price and income proxy variables to be negligible in terms of goodness of fit and forecasting, when compared to alternative univariate models.

Nordström (1999) found that prices and, in particular, changed preferences have an important influence on inbound tourism in Sweden; however, from a forecasting point of view, pure time-series models turn out to be as good as the economic models. One reason for the relatively modest short- and medium-term forecasting performance of the economic models was the difficulty in obtaining good forecasts of the price variables. Since a large part of the variation in inbound tourism in Sweden can be explained by taste changes, in Nordström (1999) estimated by a stochastic trend, the largest gain in forecasting accuracy is probably not merely the result of better prediction of the price variables. Instead, better predictions of tourism demand may be expected by estimating and forecasting tourism series jointly with other tourism series, in which information on taste and price changes are already incorporated. These predictions are also gained at a lower cost.

Since the form of such models is determined by the data alone, the analysis demands a flexible structure. As structural changes or regime shifts are important aspects of the real world, different transformations of the series should be made in order to make forecasts robust. Clements and Hendry (1996) showed that forecasts from a vector autoregression in differences (DVARs) may be more robust than models in levels with respect to certain forms of structural change. However, as pointed out by Lütkephol (1991, pp. 232-233), a linearly transformed finite order VAR(p) process will, in general, not admit a finite order VAR representation. We therefore use vector autoregressive moving average (VARMA) models to investigate whether information from different tourism series improves the forecasting performance of tourism demand models.

In this study, we focus on monthly tourism flow data that are characterised by pronounced seasonal patterns. As the identification process for VARMA models can be cumbersome for high-frequency data, as a consequence of the long lag polynomials, we begin the analysis with the univariate counterpart. The Box and Jenkins (1970) modelling framework rests on applying the seasonal difference $1-B^{12}$, where B is the back-shift operator $B^k y_t = y_{t-k}$, in the stationarity-producing phase of the procedure. Factorising the $1 - B^{12}$ polynomial as

$$1-B^{12} = (1-B)(1+B)(1+B^2)(1+B+B^2)(1-B+B^2)(1+\sqrt{3}B+B^2)(1-\sqrt{3}B+B^2)$$

shows that the seasonal difference operator implicitly imposes a root on the zero frequency, as well as on all seasonal frequencies π, $\pi/2$, $2\pi/3$, $\pi/3$, $5\pi/6$, and $\pi/6$ corresponding to the periods 2, 4, 3, 6, 12/5, and 12. For most empirical series, one would expect to find a unit root at the zero frequency and possibly at some of the seasonal frequencies (e.g., Clements and Hendry 1997, Franses 1996, Hylleberg 1992, Beaulieu and Miron 1993). Thus, there is a risk of over-differencing with the $1 - B^{12}$ filter.

We therefore start the univariate analysis with an investigation of the effects of imposing different sets of seasonal unit roots on the model. As pointed out by Clements and Hendry (1997), there is little evidence in the literature on the effect of imposing seasonal unit roots on forecast accuracy. Exceptions are some studies on quarterly data. For example, Clements and Hendry (1997) compared the forecast performance of a sequence of rolling forecasts of autoregressive models, and Paap, Franses and Hoek (1997) compared the forecast performance of autoregressive seasonal unit root models and seasonal mean-shift models. Results in Clements and Hendry (1997) indicated that imposing roots at all frequencies led to at least as good forecasting performance as did imposing the smaller number of roots suggested by the HEGY (Hylleberg, Engle, Granger and Yoo 1990) procedure. Paap et al. (1997) found, on the other hand, that the empirical seasonal mean-shift models produced more accurate forecasts than did models that incorrectly imposed too many seasonal unit roots. The simulation study in Paap et al. (1997) indicated, however, that the number of changing seasons may have some effect on the results. If one or more seasonal unit roots were present in the Monte Carlo experiment, the model selected by the HEGY procedure out-performed the seasonal mean-shift model.

This paper is organised as follows. In Section 2 we present the data on the monthly number of guest nights and utilise a state-space model to describe the components in the time series. In Section 3.1, we perform a statistical test of unit roots, and investigate whether the series become stationary after imposing the unit roots indicated by the test or by some other filter. The forecasting performance of the univariate ARMA models with different unit roots imposed is evaluated in Section 3.2. The potential improvements in forecasting performance by cross relating the series is studied in Section 4. Section 5 concludes.

2 Data

In this study we analyse the monthly numbers of guest nights spent in Swedish hotels and cottages for the five largest national categories visiting Sweden. This type of data is likely to be integrated on the zero and some seasonal frequencies, due to important long-run and seasonal components. The economics underpinning this pattern may depend on a large number of factors, such as increased leisure time, the activities undertaken by the visitors, weather conditions, the distance visitors have to travel, changing transport costs, or changing preferences. Although the underlying reason for the changing seasonal pattern is an interesting issue, it is beyond the scope of this paper.

Accommodation statistics of this kind have been collected by Statistics Sweden since January 1978, and we use this data through December 1996. In 1994, the five largest national categories were, in decreasing order, German, Norwegian, Finnish, US, and Danish visitors. A time series plot of the number of guest nights in hotels and cottages is shown in Figure 1. The figure reveals a strong seasonal pattern in all series, with the cottage series more irregular than the hotel series.

Another way of obtaining a descriptive analysis of the trend and amount of seasonal variation in the series, is to put the series in state-space form (see e.g. Harvey 1989). Here, we estimated the guest-night series on a stochastic trend and

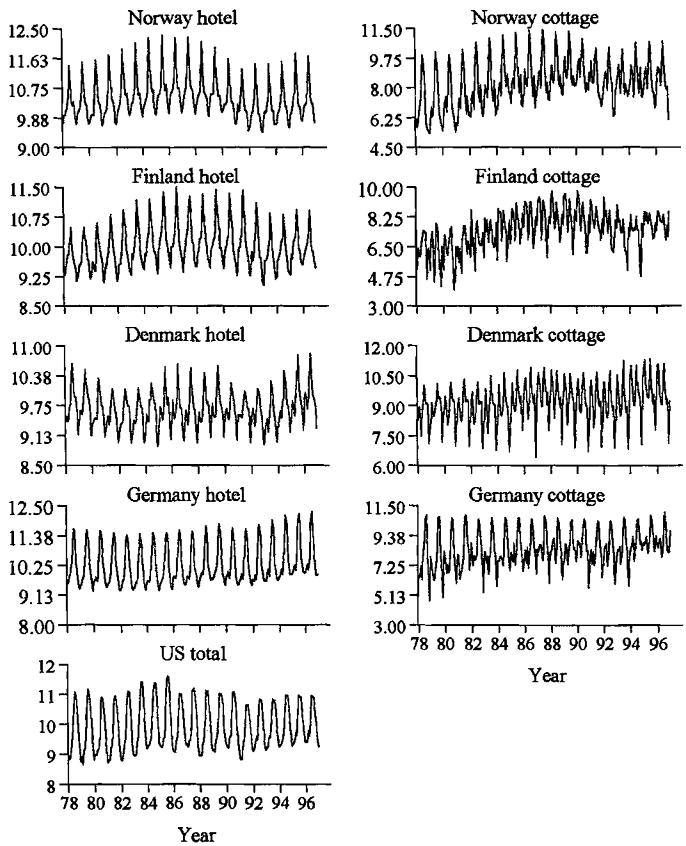

Figure 1: Natural logarithms of inbound guest nights in hotels and cottages in Sweden, 1978-96.

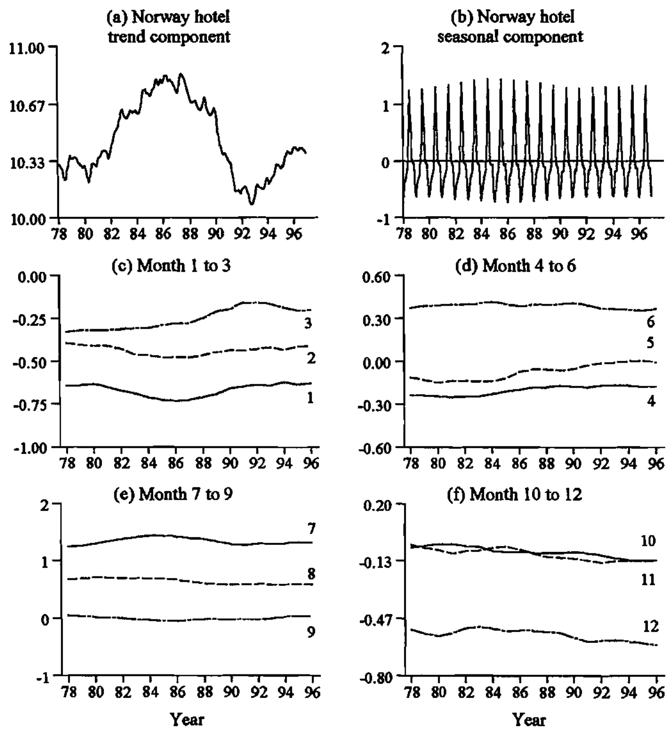

Figure 2: Trend and seasonal component of logarithms of Norwegian guest nights in hotels, (1978-96).

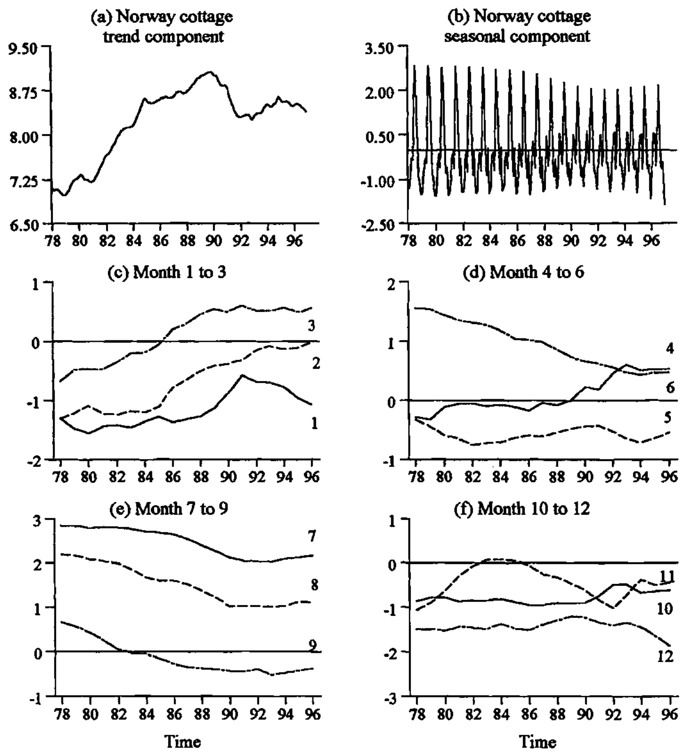

Figure 3: Trend and seasonal component for logarithms of Norwegian guestnights in cottages, (1978-96).

a stochastic trigonometric seasonal component.[1] The estimated components of the Norwegian series are revealed in Figures 2 and 3. Figures 2*a* and 3*a* indicate that the series may not be trend stationary. Therefore we expect to find a unit root at the zero frequency.

The seasonal component is plotted in Figures 2*b* and 3*b*. As revealed in Figure 2*b*, the seasonal component for the Norwegian hotel series is rather stable. The seasonal component for the Norwegian cottage series in Figure 3*b*, however, shows a changing pattern. Figure 3*b* also indicates that the amplitude of the seasonal component for the summer months decreases over the sample period. In Figures 2*c*-2*f* and 3*c*-3*f* we have plotted the seasonal contribution from each month. If the seasonal component is deterministic around seasonal intercept dummy variables, then the lines in Figures 2*c*-2*f* and 3*c*-3*f* would be horizontal straight lines. As expected, the graphs in Figure 2*c*-2*f* only reveal minor changes, hence we do not expect to find seasonal unit roots on all seasonal frequencies in the Norwegian hotel series. From the monthly contributions in Figures 3*c*-3*f*, we can see that the Norwegian cottage series is probably not deterministic around seasonal intercept dummy variables. The figure reveals increases for the months February to April, while the traditional holiday months, i.e. June, July, and August, indicate decreases. Altogether this indicates a non-constant seasonal pattern. However, at this stage we can not rule out the possibility that the seasonal component in the Norwegian cottage series is deterministic around seasonal intercept dummy variables and deterministic seasonal trends.

[1]The logarithmic accommodation series y_t have been estimated on a stochastic trend, $\mu_t = \mu_{t-1} + \xi_t$, and a stochastic seasonal component $\gamma_t = \sum_{j=1}^{6} \gamma_{jt}$, $\begin{bmatrix} \gamma_{jt} \\ \gamma_{jt}^* \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j,t-1}^* \end{bmatrix} + \begin{bmatrix} \omega_{jt} \\ \omega_{jt}^* \end{bmatrix}$ $j = 1, ..., 6$, according to $y_t = \mu_t + \gamma_t + \varepsilon_t$, where ε_t, ξ_t, ω_{jt} and ω_{jt}^* are zero mean white-noise processes which are uncorrelated with each other.

3 Testing for seasonal unit roots

To formally test for unit roots at the zero and seasonal frequencies, we use the test presented by Beaulieu and Miron (1993) [BM] and Taylor (1998). The test presented by Taylor is an extension of BM's test to allow for seasonal drifts under the null hypothesis. Taylor's and BM's procedure is analogous to the approach developed by Hylleberg, Engle, Granger, and Yoo (1990) and is based on the following regression equation:

$$\phi(B)\ \Delta_{12}\, y_t = \sum_{k=1}^{12} \gamma_k y_{k,t-1} + \sum_{m=1}^{12} \beta_m D_{m,t} + \sum_{m=1}^{12} \delta_m D_{m,t} t + \varepsilon_t, \quad t = 1, 2, ..., T. \quad (1)$$

In regression (1), the $y_{k,t}$, $k = 1, ..., 12$, constitute a set of linear filters of y_t, whose exact form is given in BM (p. 308), $D_{m,t}$ is the seasonal intercept dummy for month m, $m = 1, ..., 12$, and $\phi(B) = (1 - \phi_1 B - ... - \phi_p B^p)$ is a lag polynomial of order p. In the BM test, the third expression on the right-hand side is replaced by δt, i.e. with a common trend for all seasons. The applied filters separate out unit roots corresponding to frequencies 0, π, $\pi/2$, $2\pi/3$, $\pi/3$, $5\pi/6$ and $\pi/6$, such that the restriction $\gamma_1 = 0$ in (1) implies a zero-frequency unit root, while $\gamma_2 = 0$ implies a π or Nyquist frequency unit root, and $\pi_k = \pi_{k+1} = 0$ implies a unit root at the corresponding frequency pair $(k,\, k+1)$, $k = 3, 5, 7, 9, 11$.

The goal is to test hypotheses about a particular unit root without taking a stance on whether other seasonal or zero frequency unit roots are present. In order to test hypotheses about various unit roots, the OLS test statistics based on (1) are compared to the critical values tabulated in BM (1993) and Taylor (1998). For frequencies 0 and π, we examine the relevant t-statistic for $\gamma_k = 0$, $k = 1, 2$ against the alternative that $\gamma_k < 0$. For the other frequencies, we test $\gamma_k = \gamma_{k+1} = 0$, $k = 3, 5, 7, 9, 11$, with an F-statistic. Additional lags of the dependent variable are included to capture autocorrelation in the errors. The order p is based on LM-tests of first to 36th order of serial correlation in the residuals.

We consider different specifications of the deterministics and allow for the possibility of seasonal intercepts together with a time-trend variable or seasonal time-trend variables. This last case permits the drift in a seasonal random walk data generating process (DGP) to differ across seasons, thereby allowing the amplitude of the variations across the seasons of the deterministic component in the level of the time series to vary (linearly) over time. One further implication of the seasonal trends formulation in (1) is that it allows one to test the unit root null hypothesis against the alternative of trend stationarity not only at the zero frequency, but also at the seasonal frequencies (Smith and Taylor, 1999). The latter tests are not possible with the formulation of BM.

3.1 Test results

Initially all series were tested with Taylor's (1998) approach using both seasonal dummies and trends. An F-test could not reject the null of separate seasonal trends at a 10 percent significance level for any of the series. However, Figure 3 indicates that seasonal trends may be appropriate for the Norwegian cottage series. In the following, we base our analysis on BM's test as we do not wish to include unnecessary deterministic seasonal components in the test (see Taylor, 1997). As the F-test ruled out the seasonal trends specification, we assume that the BM test has the same alternative hypothesis as Taylor's test. Since there is no clear-cut evidence whether the Norwegian cottage series have deterministic seasonal trends or not, we tabulate results from both BM's and Taylor's specification for this series.

In Table 1, the outcome of seasonal unit root tests using the BM (1993) specification is presented. The results are based on data up to 1994:12. Results indicate that the non-seasonal unit root appears to be present in all time series. In addition, the BM tests reveal that most of the series have one or two seasonal unit roots, indicating a changing seasonal pattern caused by seasonal stochastic trends. For the hotel series and US total series, results are the same as when seasonal trends are included, an exception is the Danish hotel series were unit roots at the $\pi/2$ and $2\pi/3$ frequencies where indicated in addition to the roots revealed in Table 1. However, for *all* cottage series there is a difference in the number of identified unit roots, depending on whether a common trend or seasonal trends are included in the test. At a 5 percent significance level, the unit root test with seasonal trends indicated a unit root at the zero frequency and trend-stationary seasons.

For the US series and German cottage series, Table 1 indicates a deterministic

Table 1: Results of tests for seasonal unit roots.

		0	π	$\pi/2$	$2\pi/3$	$\pi/3$	$5\pi/6$	$\pi/6$
Series	Lag	γ_1	γ_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Norway hotel	3	1.95	-3.39	13.23	18.94	9.41	11.23	3.39
Finland hotel	1	0.75	-3.62	8.75	9.95	15.46	6.94	4.53
Denmark hotel	-	-1.25	-3.69	8.00	10.87	7.39	4.87	13.28
Germany hotel	-	-0.11	-3.93	8.48	15.57	3.84	9.42	7.78
Norway cottage	-	1.26	-3.74	7.64	10.36	8.14	10.94	2.64
Finland cottage	-	-0.21	-3.86	9.63	16.24	15.51	4.42	8.17
Denmark cottage	2	-0.80	-5.31	5.95	10.10	3.46	10.00	2.51
Germany cottage	-	-2.05	-3.84	8.00	13.81	6.24	11.61	7.23
US total	-	3.06	-4.74	20.52	20.91	19.56	21.16	12.94
Norway cottage*	1, 12, 24	0.27	-3.90	10.77	15.78	15.53	15.75	9.75

Notes:*Seasonal dummies and seasonal trends have been included in the unit root test, otherwise seasonal dummies and a common trend have been included in the unit root test. The critical values at the percent level of the common trend and seasonal dummies are γ_1 = -3.28, γ_2 = -2.75, and F = 6.23. The critical values at the 1 percent level of the common trend and seasonal dummies are γ_2 = -3.31, and F = 8.33. * The critical values at the 5 percent level of the seasonal trends and dummies are γ_1 = -3.32, γ_2 = -3.31 and F = 9.13. * The critical values at a 1 percent level of the seasonal trends and dummies are γ_2 = -3.86 and F = 11.56. Lag indicates which lag of $\phi(B)y_{13t}$ is included.

seasonal pattern around seasonal intercept dummies. This is possibly due to longer travel time or distance for these trips, which suggests that they are undertaken during a longer vacation period. For none of the logarithmically transformed time series does the BM test in Table 1 indicate use of the $1 - B^{12}$ differencing filter.

The robustness of the test result has been checked by re-estimating (1) over the full sample. Generally, the same unit roots were found. Exceptions were the Norwegian and Danish hotel series, for which additional seasonal unit roots were found. As pointed out by Perron (1990) and Franses and Vogelsang (1998), an increased number of unit roots can be a result of neglected deterministic mean shifts, and at a 5 percent significance level we identified a mean shift for both series in 1994. The test for the Norwegian hotel series may also suffer from low power, since we have to increase the order of the lag polynomial to 5 (lags 1,3,4, and 5) (Hylleberg 1995).

To see whether the series become stationary after imposing the identified roots in Table 1, the filtered series are again tested for unit roots. That is, for the Norwegian and Finnish hotel series we impose roots on the zero and $\pi/6$ frequencies with the filter $(1-B)(1-\sqrt{3}B+B^2)$, for the Danish hotel series on the zero and $5\pi/6$ frequencies with the filter $(1-B)(1+\sqrt{3}B+B^2)$, and so on for the other series. Results indicate that only in one case (Norwegian holiday villages) do these filters lead to a stationary series. Generally, on the filtered series we found unit roots at both the zero frequency and some of the seasonal frequencies. However, after reducing the identified filter to $1-\sqrt{3}B+B^2$ for the Norwegian and Finnish hotel series we obtained stationarity. The same filter also turned out to generate stationary processes for all series in Table 1 that have one or more seasonal unit roots. On the other hand, imposing roots at all frequencies, as implicitly recommended by the Box-Jenkins approach, tests indicated that a unit root was generally identified at the zero frequency. Only the German and Finnish holiday villages series become stationary using the $1-B^{12}$ difference.[2]

3.2 Forecasting performance

In this section we estimate univariate ARMA(p,q) models to compare the forecast accuracy between models where the smallest number of unit roots has been imposed to obtain a stationary series, to that of a series where unit roots have been imposed at all frequencies. The ARMA models to be estimated are written as

$$v(B)y_t = v(B)\left(\sum_{m=1}^{12}\varphi_m D_{m,t} + \phi^{-1}(B)\theta(B)u_t\right),$$

for the models based on the $1-B$ difference and the BM test, whereas the models corresponding to the DGP of Taylor's test are written as

$$v(B)y_t = v(B)\left(\sum_{m=1}^{12}\varphi_m D_{m,t} + \sum_{m=1}^{12}\lambda_m D_{m,t}t + \phi^{-1}(B)\theta(B)u_t\right),$$

where $v(B)$ is the filter applied to the series, $\phi(B) = 1-\phi_1 B - ... - \phi_p B^p$ and $\theta(B) = 1+\theta_1 B + ... + \theta_q B^q$. To obtain a stationary process the annual frequency

[2]However an F-test over all frequencies indicate stationarity using a 12^{th} difference (at a 5 percent significance level).

filter, $1-\sqrt{3}B+B^2$, has been applied to all series, except the German cottage and US total series to which a first difference has been applied. The German cottage series became stationary once a first difference was imposed, and for the US total series the first difference turned out to be the best alternative to a twelth-difference, although the BM test indicated a root on the $\pi/6$ frequency.[3] To identify the models we started with a general ARMA(p,q) model, with an initial lag structure (p,q) of three years. This tentative specification was thereafter gradually reduced by minimising the Schwartz Bayesian information criterion (BIC), controlling for autocorrelation in the disturbances.

The ARMA models are estimated by non-linear least squares using EViews 2.0. The estimation results, which are available from the authors upon request, suggest that the $1-B^{12}$ transformed series generally have roots close to one in the MA polynomial, which is to be expected since the BM tests indicate that the series are over-differenced. On the other hand, the models with the smaller number of imposed unit roots have roots close to one in the AR polynomial. The results also indicate that the models for the $1-B^{12}$ transformed series have a more parsimonious parameter representation than models based on other filters.

The forecasts are obtained as follows. The identified models are estimated on data up to 1994:12. Then, 1994:12 is taken as the forecast origin for forecasting 1 up to 12 steps ahead. The model is then re-estimated on data up through 1995:1, with the form of the model unchanged. 1995:1 is then taken as the forecast origin, and so on, subject to the constraint that we have data on the period being forecasted (the sample ends in 1996:12). This gives 24 one-step forecasts, 23 two-step forecasts, and so on. The forecasts are then transformed from the differentiated form to forecasts in log levels. By comparing the forecasts in levels we do not need to calculate the generalised forecast error second moment (GFESM) measure developed by Clements and Hendry (1993). The means, variances, and mean square errors are then calculated on the forecast error for each forecast horizon.

In Figure 4 we have plotted the mean squared forecast errors (MSFE) for each forecast horizon. As the figure reveals it is more difficult to obtain good forecasts for

[3]The BM test indicates that other seasonal filters yield unit roots at several seasonal frequencies.

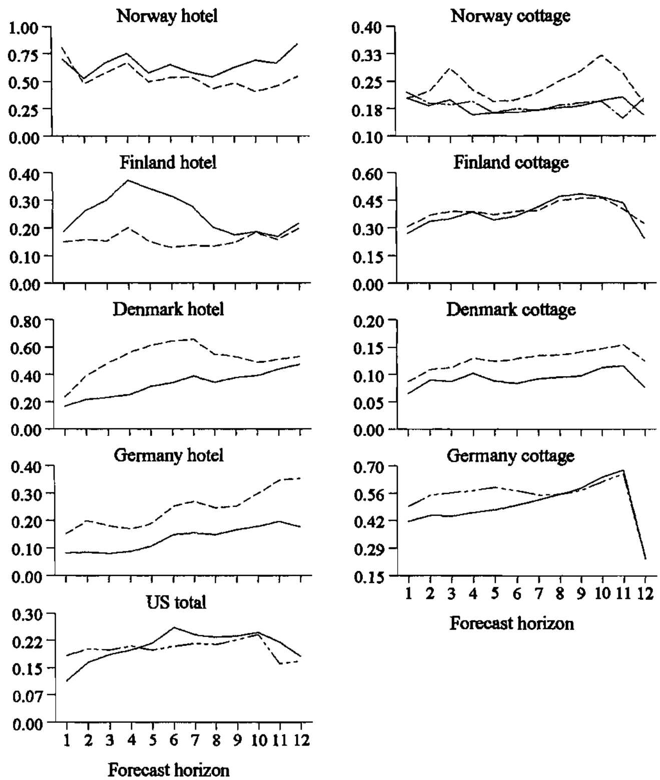

Figure 4: Mean square forecast error for the logarithmic series in levels. Solid line $(1 - B^{12})$-differentiated series; broken line $(1 - \sqrt{3}B + B^2)$-differentiated series; broken line with double dots $(1 - B)$-differentiated series; broken line with dots $(1 - B)$-differentiated series with seasonal trends. The MSFE for the Norwegian hotel series have been multiplied by 100; the MSFE for the other hotel series and the US total series have been multiplied by 10.

the cottage series compared to the hotel series. Although the difference in forecast performance between the different filters is small, the $1 - B^{12}$ filter (solid line) generally produces the smallest MSFE. The figure also indicates that the Norwegian cottage model based on a $1-B^{12}$ difference or a $1-B$ difference and seasonal trends produces equally good forecasts. The calculated variance of the forecast errors shows the same pattern as the MSFE but is smaller for the $1 - B^{12}$ differentiated series in all cases except for the Finnish hotel series. The mean of the forecast errors, however, indicates that the filter with the smaller number of imposed unit roots yields better forecasts in six out of nine cases.

However, the calculated mean of the forecast errors indicate a tendency to under-estimate the actual number of guest nights, especially for the $1-B^{12}$ differentiated series. Whether the under-estimation is a result of an increasing positive trend in the underlying series or a result of a bias in the parameter estimates is difficult to say. According to Granger (1996), there is a tendency to under-estimate change. We have therefore performed a small Monte Carlo study for the $(1-\phi B)y_t = (1-\theta B^{12})u_t$ process to study the small sample properties of the estimator.[4] The results indicate that there is a bias towards zero for the AR parameter, which increases as the absolute value of the autoregressive parameters increases. The bias also increases as the absolute value of the moving average parameters increases, but to a smaller extent. However, the bias was never found to be larger than two standard deviations. In the positive autoregressive parameter space with $\theta = -0.6$ and $n = 240$, the 6-steps ahead forecast error has a mean ranging from -0.06 to -0.02. For the same parameter settings, the empirical mean squared forecast error (EMSFE) for 6 steps ahead is 3% larger than the theoretical MSFE, $\sigma_u^2(1 - \phi^{2\times 6})/(1 - \phi^2)$, when $0 < \phi \leq 0.6$, 6-10% larger for $0.7 \leq \phi \leq 0.9$, and 15% larger for the unit root case, $\phi = 1$. Thus, to some extent the under-estimation of the number of guest nights is a result of a downward bias in the autoregressive parameters.

[4] We employed four sample sizes $n = \{60, 120, 240, 480\}$ and conducted 1000 replications in the parameter space [-1,1] with an interval of 0.1.

4 Can the quality of the forecast be improved?

Since the results in the previous section indicated that the $1 - B^{12}$ difference was preferable, compared to other seasonal filters, we here study the effects of adding information from other tourism series to the 'Box-Jenkins' ARMA model. As tourism series for different countries tend to correlate, and these series contain information from prices, income and other sources, the forecast performance may be improved by joint modelling.

To see whether the forecast accuracy can be improved for the Finnish hotel series and the Norwegian cottage series, we estimate vector ARMA(p, q) models

$$\mathbf{A}(B)\mathbf{y}_t = \mathbf{M}(B)\mathbf{u}_t, \tag{2}$$

where $\mathbf{A}(B) = \mathbf{A}_0 - \mathbf{A}_1 B - ... - \mathbf{A}_p B^p$, $\mathbf{M}(B) = \mathbf{M}_0 + \mathbf{M}_1 B + ... + \mathbf{M}_q B^q$ are matrix polynomials in B, and correspond to the VAR and MA operators respectively. $\mathbf{y}_t$ is a K-dimensional time series $y_{1t}, ..., y_{Kt}$ and $\mathbf{u}_t$ is a K-dimensional white noise disturbance process with mean zero and non-singular covariance matrix $\mathbf{\Omega}$. $\mathbf{A}_i$ and $\mathbf{M}_j$ are $(K \times K)$ dimensional coefficient matrices, and $\mathbf{A}_0$ is lower-triangular with ones on the diagonal.

Specifying the VARMA process requires that identifying restrictions of some kind are imposed. Since the monthly data results in rather long lag polynomials, the model specification procedures advocated by Hannan and Kavalieris (1984) or Poskitt (1992) were of limited value. Instead, we used prior information about the univariate processes obtained from the Box-Jenkins approach for each series. To this tentative specification, additional VARMA components identified from the sample partial autocorrelation matrix function and sample autocorrelation matrix function were added. This preliminary model was thereafter estimated in echelon form (e.g., Hannan and Deistler 1988, Lütkepohl and Poskitt 1996), whereafter additional (zero) restrictions were imposed on "insignificant" parameters to reduce the parameter space. All VARMA models were estimated with the program *MulTi* (Haase et al. 1992).

To see whether (2) is an adequate representation of the process for the differenced series or whether a cointegrating component should be added to the model, we used

Table 2: Estimated parameters of the echelon VARMA representation.

Series	$\mathbf{A}_1$		$\mathbf{A}_3$		$\mathbf{A}_8$		$\mathbf{M}_{12}$	
Norway hotel	0.60 (0.06)	0	0.19 (0.07)	0.03 (0.05)	0.15 (0.06)	−0.05 (0.05)	−0.52 (0.07)	−0.02 (0.06)
Finland hotel	0	0.34 (0.06)	0.10 (0.07)	0.15 (0.07)	0.15 (0.08)	0.14 (0.06)	0.11 (0.09)	−0.57 (0.07)
	$p_6 = 0.73$, $p_{12} = 0.57$, $p_{18} = 0.28$.							
	$\mathbf{A}_1$		$\mathbf{A}_{12}$		$\mathbf{A}_{24}$		$\mathbf{M}_{12}$	
Norway hotel	0.48 (0.08)	−0.09 (0.12)	0.32 (0.10)	0	0	0	0.11 (0.14)	−0.23 (0.16)
Norway cottage	0.04 (0.04)	0.20 (0.08)	0	0	0.23 (0.03)	0	0.38 (0.05)	−0.62 (0.09)
	$p_6 = 0.86$, $p_{12} = 0.85$, $p_{18} = 0.80$.							

Notes: Standard error within parentheses. p_k = p-value of portmanteau statistic based on k lags. The Norwegian and Finnish hotel model estimates the growth rate. The bivariate Norwegian hotel and cottage model estimates the annual changes (the series has not been log transformed).

Johansen's (1991) test for cointegration. Results by Saikkonen (1992) and Saikkonen and Luukkonen (1997) indicate that Johansen's test remains valid even if the actual data generating mechanism is a mixed VARMA process. To test for cointegration on the zero frequency the seasonal filter $S(B) = \sum_{j=0}^{11} B^j$ was applied to the series, to remove any seasonal unit roots.[5]

For both the bivariate model of annual growth rates for Norwegian and Finnish guest nights on hotels and the model consisting of Norwegian guest nightss in hotels and cottages for annual changes (the series have not been log transformed), cointegration at the zero frequency is rejected at the five percent significance level.[6]

[5]At present there is no test available for seasonal cointegration for monthly data. For quarterly data see, for example, Johansen and Schaumburg (1998).

[6]For the Norwegian hotel and cottage series in levels, the BM test indicates unit roots at all frequencies. After a $1 - B^{12}$ difference, the series turned out to be over-differentiated, with a unit root on the zero frequency.

As can be seen in Table 2, additional information (compared to the univariate ARMA model) in the estimation of the growth rate of the Finnish hotel series comes from the annual growth rate of the Norwegian hotel series at AR lags 3 and 8, and MA(12). An additional AR component of the Finnish hotel series at lag 8 is also included. In the analysis of the bivariate Norwegian model of annual changes in the hotel and holiday villages an AR(24) lag was identified from the sample partial autocorrelation matrix function.

4.1 How far ahead can we forecast?

Since the R^2 statistic for an ARMA model can be defined as one minus the ratio of the residual variance to the total variance of the series, it can be seen as a measure of the relative predictability of a time series, given its past history (Nelson, 1976). For a forecast of a stationary series, we find an equivalent measure of the amount of information in Parzen's (1981) prediction variance horizon (PVH). Extending this kind of information measure to the multivariate case (Oke and Öller 1997), we obtain a measure for the amount of information in an h-step ahead forecast for series i, as

$$I_i(h) = 1 - \frac{\sum_{j=0}^{h-1} \sum_{k=1}^{K} \Psi_{ik,j}^2 \sigma_{uk}^2}{\sum_{j=0}^{\infty} \sum_{k=1}^{K} \Psi_{ik,j}^2 \sigma_{uk}^2}, \tag{3}$$

where Ψ_{ik} is the ik^{th} element in a $(K \times K)$ matrix polynomial from the Wold representation of the VARMA process (2). The variance of the i^{th} series h-step ahead forecast error is given by the numerator where σ_{uk}^2 is the k^{th} diagonal element of $\mathbf{\Omega}$, with $K = 1$ in the univariate case. Just as the R^2 in multiple regression can be used to test joint hypotheses, we can use an estimate of (3) to test if the forecast h-steps ahead contains any information

$$\zeta_i = \frac{T - \eta_i - 1}{\eta_i} \frac{\hat{I}_i(h)}{1 - \hat{I}_i(h)}, \tag{4}$$

where ζ_i is approximately F-distributed with η_i and $(T - \eta_i - 1)$ degrees of freedom (Nelson 1976), and η_i is the number of estimated parameters in the i^{th} equation. Solving for $\hat{I}_i(h)$ in (4) and using the same statistical decision rule as in Parzen

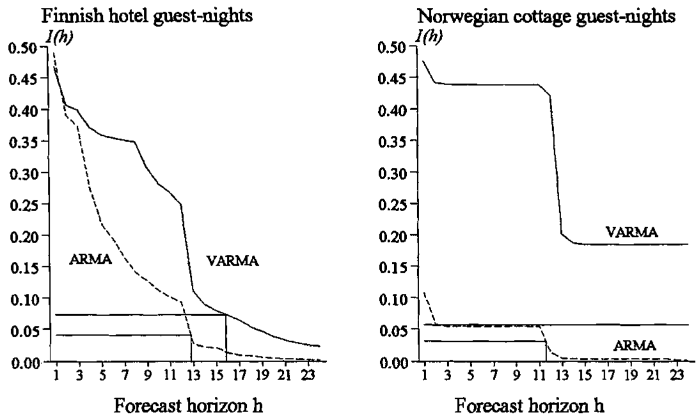

Figure 5: Amount of information $\hat{I}(h)$ in forecasting growth rates for Finnish hotel guest nights and changes in Norwegian cottage guest nights.

(1981) and Öller (1985) the short memory of the VARMA model is that h for which

$$\hat{I}_i(h) \geq \omega_{i,a}, \quad \hat{I}_i(h+1) < \omega_{i,a} \tag{5}$$

with a as the significance level and

$$\omega_{i,a} = \frac{F_a(\eta_i, T-\eta_i-1)}{\{F_a(\eta_i, T-\eta_i-1) + (T-\eta_i-1)/\eta_i\}}. \tag{6}$$

Comparing the amount of information in Figure 5, it is seen that $\hat{I}(h)$ is higher for the VARMA forecasts.[7] For example, the VARMA forecast for the Finnish hotel series has the same amount of information after about 11 periods as the ARMA model has after approximately 4 periods. From the figure it can also be seen that the VARMA forecast for the Norwegian holiday villages series contains more information after 24 steps than the ARMA forecast after one step.

At a 5 percent significance level the critical values $\omega_{i,a}$ (marked with a dotted line) for the ARMA and VARMA forecast for the Finnish hotel series in Figure 2

[7]Both the ARMA and VARMA models have been estimated in MulTi.

become 0.041 and 0.073, respectively. From (5) the forecast horizon for the ARMA model is 12 steps and for the VARMA model 15 steps. For the forecasts of the Norwegian holiday villages series, the critical values are 0.031 for the ARMA model and 0.057 for the VARMA model. These correspond to forecast horizons of 11 and more than 24 steps, respectively.[8]

To see whether the VARMA models are also preferable in an out of sample comparison, we have used the same evaluation criteria as for the univariate models, i.e., rolling 12 step ahead forecasts. For the Norwegian holiday villages series, the MSFE for the VARMA model was lower in three out of 12 forecast horizons 1, 10 and 11 steps ahead. Furthermore, the bias was always found to be (positively) larger for the bivariate model. For the Finnish hotel series we found a similar result, with smaller MSFE and bias for the bivariate forecasts in four respectively five out of 12 forecast horizons corresponding to 1, 3, 4, 5 respectively 1, 9, 10, 11, 12 steps ahead. This seemingly unfavourable result for the bivariate models is possibly due to structural breaks in one or both of the series at the end of the sample period, or over the forecast period.

5 Conclusions

In this study it has been indicated that ARMA models built conditionally on the outcome from seasonal unit root test do not produce more accurate forecasts than models that *a priori* impose unit roots at the zero and all seasonal frequencies. Although the procedure to impose roots on all frequencies results in a misspecified model, this approach gives more parsimonious models and generally produces more accurate short-term forecasts. This corresponds to the results in Clements and Hendry (1997), but is not in agreement with the results in Taylor (1997) who found little difference between models with different sets of unit roots imposed. One reason for the better forecast performance of the $1 - B^{12}$ differenced series may be due to shifts in deterministic factors over the forecast period.

[8] We have also used seasonally adjusted industrial production as a proxy variable for income, to see whether the forecast could be improved. The result indicates that the informative forecast horizon increases somewhat, but not by much. These results are not reported.

Unit roots were generally indicated on the zero and some of the lower seasonal frequencies. Imposing the roots indicated by the unit root test generally resulted in a non-stationary series. Although the presence of a unit root can be of particular interest, e.g. in the search for co-integration, it is unlikely that a test for unit roots is the main objective for the analysis. In practice we do not know whether a unit root really exists, or whether the degree of differencing changes over time. So rather than carrying out a unit root test, it is better to choose a flexible model structure, e.g. a state space model, that can handle features such as changing trend and seasonal patterns.

In the identification stage of the seasonal VARMA models on $1 - B^{12}$ differenced series, the specification procedures advocated by Hannan and Kavalieris (1984) and Poskitt (1992) turned out be of limited value. Instead, we found the Box-Jenkins (1970) and Tiao and Box (1981) approaches more practicable. Results from the VARMA models indicate that information from other tourism series may improve the forecast accuracy of tourism demand. In the estimated models, the short memory for the Finnish hotel series and Norwegian holiday villages series was prolonged by three months and more than one year respectively, by cross relating the time series. The out-of-sample comparison indicated, however, that the univariate models may be preferable. This highlights the fact that multivariate models do not necessarily give better predictions and that in-sample and out-of-sample evaluation criteria can give different results.

Considering the different estimation techniques presented in this study, univariate ARMA models with different unit roots imposed and VARMA models, we recommend the seasonally differenced $(1-B^{12})$ univariate ARMA model for short-term forecasts for the practitioner. Not only does this technique produce equally good forecasts as the other techniques, but it also does it to a lower cost. First of all, we do not need to estimate the seasonal unit root test and secondly we can estimate the model using any conventional time series program.

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