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The Dynamics of European Industrial Structure

by

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Abstract

Has the European integration process lead to increased specialisation and what drives changes in specialisation? To address these questions we apply a model that incorporates endowments, technology and increasing returns to scale (IRS). Analyses reveal that countries with high capital accumulation have become increasingly specialised in capital-intensive industries; this holds for both human and physical capital while countries have diverged (converged) in physical (human) capital abundance. No increased concentration of IRS industries to large markets is found. Analysing R&D indicates scale economies in R&D at the firm level and that firm level R&D is what drives competitiveness. Finally, there is robust evidence for a domestic interdependency in industries specialisation patterns.

Keywords: Specialisation; Productivity; Trade; Technology; Technology transfers; R&D
JEL classification: C29; F12; O33; O52

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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. Some 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 (IRS)*.

One feature that distinguishes this model from the vast majority of trade models is that technological progress is endogenous by 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 inter-industry technology transfers and through 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 in 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

[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.

in countries' specialisation. This simple device may give us interesting information about the forces behind changes in countries' specialisation patterns.

Empirical tests of the factor proportion model, beginning with Leontief (1954) and onward 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 of innovative activity affecting export patterns and the former a stronger relationship between technological variables and exports compared to the impact of labour productivity on exports.

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. Davis and Weinstein (2001) elaborate the H-O model by allowing for technological differences and intermediate goods. Hakura (2001) investigates the role of technological differences and the failure of the H-O-V model when analysing a set of EC countries.

Harrigan (1997) and Gustavsson *et al* (1997) specify models 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

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

further by empirically relating technology to R&D, technology transfers and learning.

The link between R&D, productivity, and trade, is a field where there are numerous empirical studies. Keller has studied these links in a series of articles (see for example, Keller 1997, 2000). 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 (1974) uses the capital and intermediate input matrix to proxy closeness of industries[5].

During the last decade, economists have rediscovered geography as a determinant for specialisation. Marshall (1920) argued that the decision for the location of industrial activities is affected by three categories of returns to agglomeration. Briefly, he argued for: (1) spillovers that loosely speaking are 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 been labelled *the new economic geography literature*[6]. The new economic geography has inspired a set of empirical papers that 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) examines 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 increasing return to scale industries, while the evidence is mixed for other industries.

In this study we analyse ten European countries (nine of which are members of the EU at the end of the sample period) and 22 industries spanning the period 1976-96.

Econometric analyses reveal that *cumulating productive factors* such as human and physical capital turn countries towards an increased

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[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).

specialisation in industries in the factor they accumulate relatively much of. On the accumulation of capital there is evidence of an increased concentration of capital-intensive industries in initially capital-abundant countries. Those capital-abundant countries also exhibit the largest increase in their capital to labour ratio. On the other hand, for human capital there is a tendency for a catching-up or convergence in human capital abundance among the countries in the sample.

In the analysis of the impact of R&D, 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 that the total R&D stocks of industries or countries to have any impact on the growth in the coefficient of specialisation.

In tracing domestic technology transfers using I/O matrices, we find quantitatively small but significant inter-industry technology transfers.

Robust evidence of domestic inter-industry interdependence in the error term was also detected. The interdependency in the error term is proportional to the I/O coefficients in 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. This may be better known as 'common shocks'.

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 $n = 1,\ldots,N$ and J countries $j = 1,\ldots J$. Each firm $f_{nj} = 1,\ldots,F_{nj}$ produces a differentiated good using V factors of production $v = 1,\ldots V$. 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 and no transportation cost. On the factor market, we assume perfect competition. Assuming a generalised

[7] In the empirical framework, human capital is treated as country-specific.

Cobb-Douglas technology, the production function for firm *f* in country *j* and industry *n* may be written as

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

where *A* is an index of technology, *v* is a factor of production, α is an intensity parameter and returns to scale are given by

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

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, α_{vn} 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].

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

c is unit cost, y_{fnjt} is firm size, and w_{vjt} is the price of factor *v* in country *j*. If all firms in an industry in a country are identical, the firms' unit cost is the same as the industry's 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. This gives the following total demand of products from country *j* and industry *n*[10].

$$D_{njwt} = \frac{F_{njt} p_{njt}^{-\sigma_n} \theta_n E_{wt}}{P_{nt}^{1-\sigma_n}} \; ; \; P_{nt} \equiv \left(\sum_{j=1}^{J} F_{njt} p_{njt}^{1-\sigma_n} \right)^{1/1-\sigma_n} . \qquad (4)$$

D_{njwt} is world demand from the *n*th industry in country *j* in year *t*, F_{nj} is the number of firms in industry *n* in country *j*, p_{njt} is the price of goods from

8 See also, Gustavsson *et al* (1999).
9 Spence (1976), and Dixit-Stiglitz (1977).
10 See Helpman & Krugman, 1985, p 206.

firms in industry n in country j, θ_n is the budget share allocated to products from industry n, E is expenditures, w is shorthand for the world, $\sigma_n > 1$ is the elasticity of substitution among products in the nth industry, 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.

$$r_{njt} \equiv \frac{Q_{njt}}{C_{njt}} = \frac{C_{njt} + X_{njwt} - M_{njwt}}{C_{njt}} = 1 + \frac{X_{njwt} - M_{njwt}}{C_{njt}}. \tag{5}$$

Q is gross value of production, and X_{njwt} and M_{njwt} are export and import in the nth industry in country j respectively; we note that $C_{njt} = \theta_n y_{jt}$. Using demand, as specified in Eq. (4), and the definition of the coefficient of specialisation as stated in Eq. (5), we get the following expression for the log of the coefficient of specialisation:

$$\ln r_{njt} = (1-\sigma_n)\ln p_{njt} - (1-\sigma_n)\ln P_{nt} + \ln F_{njt} + \ln \frac{E_{wt}}{E_{jt}}. \tag{6}$$

By monopolistic competition, unit cost equals price and we insert the expression for the log of unit cost in Eq (3) (using the assumptions of same technology across domestic firms within an industry) into Eq. (6) and get the following expression for the growth rate in the coefficient of specialisation.

$$\begin{aligned} \Delta_t \ln r_{njt} &= -(1-\sigma_n)\Delta_t \ln P_{nt} + \Delta_t \ln \frac{E_{wt}}{E_{jt}} + \Delta_t \ln F_{njt} \\ &- (1-\sigma_n)\mu_n^{-1}\Delta_t \ln A_{njt} + (1-\sigma_n)\sum_{v=1}^{V} \frac{\alpha_{vn}}{\mu_n}\Delta_t \ln w_{vjt}. \\ &+ (1-\sigma_n)\frac{1-\mu_n}{\mu_n}\Delta_t \ln y_{fnjt} \end{aligned} \tag{7}$$

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

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[11] The right hand side variables in 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),

2.3. Endogenous technology

In the expression for the coefficient of specialisation, the state of technology is exogenous. In the following 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.

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_{nj}, 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*.[13] 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

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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.

[12] In the following, we suppress time indices if they are not necessary for understanding the context.

[13] For innovations to be drastic we require for all $n \in N$, $\gamma > \alpha_{nx}^{-\alpha_{nx}}$.

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 (AGR_{nj}), is

$$AGR_{nj} = \ln(\gamma^{\alpha_{xn}})\lambda H^{ss}_{nj2}. \quad (8)$$

From Eq. (8) 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*, $\bar{H}^{ss}_{\bullet nj2} = (1/F_{nj})\sum_{f=1}^{F_{nj}} H^{ss}_{fnj2}$ 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.

2.3.2. Technology transfers and I/O linkages

Assume now that the final good is also used as an input in other domestic industries' final good production. With 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}. It is therefore possible for an innovation to increase productivity more in other industries than in the innovating industry itself, a finding that applies to the empirical R&D productivity literature.[14] 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[15]

[14] See, for example, Griliches (1992).
[15] The solution of the model is given in Appendix 1.

$$\text{AGR}_{\text{nj}} = \lambda \ln(\gamma) \left[\alpha_{xn} H_{nj2}^{ss} + \sum_{\substack{s=1 \\ s \neq n}}^{N} \alpha_{ns} H_{nj2}^{ss} \right] \qquad (9)$$

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. (7), we specify a regression equation and replace growth in the technology index with its corresponding expression derived in Eq. (8). The theoretical model gives a precise prediction of the source of technology growth, namely the number of R&D workers[16]. 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, that the right hand side variables in row one in Eq. (7) are suppressed to dummy variables and we write the corresponding regression equation with no technology transfers as

$$\begin{aligned} \Delta_t \ln r_{njt} &= \beta_0 + \beta_1 (R\&D) + \beta_2 \left(\mu_n \Delta_t \ln y_{fnjt}\right) \\ &+ \sum_{v=1}^{V} \beta_{3v} \left(\alpha_{vn} \Delta_t \ln w_{vjt}\right) + \sum_{t=1}^{T-1} \beta_{4t} D_t + \sum_{n=1}^{N-1} \beta_{5n} D_n + \sum_{j=1}^{J-1} \beta_{6j} D_j + \varepsilon_{njt}. \qquad (10) \end{aligned}$$

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 replace Eq. (8) with Eq. (9) in the regression equation[17]. We may also allow for domestic, inter-industry interdependent residuals.

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

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

3. Variables

Technology, and technology transfers

Superior technology or know-how in a certain industry generates a competitive edge over competitors. Productivity growth in the model is 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[18].

Drawing on 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[19].

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 the 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-specific R&D stock, $(S)_{fnjt}$, is the industry's R&D stock per value added, $(S/VA)_{njt}$, obtained by 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[20]. A panel with the actual number of firms in industries and countries may have been a better tool for downscaling the industries' R&D stocks but we do not have data of this type[21].

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 autoregressivity makes small deviations from the exact timing of the impact lag of R&D less severe and the stock and flow R&D measures

18 For a survey see Stoneman (1995).

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

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

21 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.

correlated, i.e. industries' R&D stocks per value added resemble an upscaled version of their R&D intensities.[22]

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 may 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 in such a way that each row is equal to one[23]. With the aid of row standardising, we are able to interpret the estimated coefficient in economic terms. The input matrix V^{in} is then multiplied by the R&D variables[24].

Endowments

The theoretical framework is based on national factor prices w_{vj}. It is difficult to find comparable cross-country time series on 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[25]. Gustavsson *et al* (1999) found a negative significant correlation between countries' endowments and national factor prices for factors when both prices and endowments were 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 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 is 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 μ_n is interacted with firm size, y_{fnjt}, $\mu_n \times y_{fnjt}$. The interpretation is that in industries with strong IRS, countries with large firms will have a comparative advantage because of low unit cost. We do

[22] The correlation between industries R&D stock per value added and R&D per value added is 0.71.

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

[24] See Appendix 2 for details.

[25] For details, see Ethier, (1984).

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, μ_n, measured as average plant size $(Q)_{nj}$/(number of establishments)$_{\mathrm{nj}}$), where Q is the value of gross output. This time invariant measure of IRS is interacted with the corresponding industries' value added $(VA)_{njt}$, $(\mu_n \times \ln(VA)_{\mathrm{njt}})$, where $(VA)_{njt}$ is a proxy for industries' market size[26]. 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 of 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, $[\tilde{\mu}_n \Delta_t \ln(VA)_{\mathrm{njt}}]$, that catches the growth rate of market size. If countries with industries that significantly increase output systematically do so because net export in IRS industries has, on average, grown faster than domestic demand, this implies a positive sign for the estimated coefficients[27].

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[26] 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 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.

[27] Formally, if we define r_x = r-1, we have $\dot{r}_x / r_x = \dot{N}x / Nx - \dot{c}/c$, hence if net export grows faster than domestic demand, the coefficient of specialisation increases. An alternative way to look at the problem is to use $\dot{r}/r = \dot{Q}/Q - \dot{C}/C$. 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.

4. Results

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

In Figure A3.1, changes in specialisation are plotted against initial levels of specialisation. If specialisation generally has increased over time, observations will be concentrated in the upper right and lower left quadrant of the figure. A pattern of this type 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, trade 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 difference out industry and country time invariant effects as well as time invariant measurement errors. By analysing changes we may 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. The applied spatial GMM error model estimator cannot handle unbalanced panels; therefore due to missing values the number of observation is reduced from 880 to 707 observations[28]. The regressions are presented in Table 1. To allow for an impact lag and to reduce noise, most variables are lagged averages over two to three years[29].

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

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

	Mod 1	**Mod 2**	**Mod 3**	**Mod 4**	**Mod 5**	**Mod 6**
Additional hypothesis ⇒	Basic model	Common shocks	R&D-stock/VA	Industry R&D stock		R&D spillovers
(Variable): [E sign][A] Hypothesis	OLS Robust	GMM-G[B]	GMM-G	GMM-G	GMM-G	GMM-G
$(\ln \alpha_{Hn} \Delta_t \ln H_{jt})$ [+] Acc human capital	0.0091 (1.27)	0.0100 (2.13)**	0.0090 (1.90)*	0.0113 (2.38)**	0.0092 (1.95)*	0.0092 (2.08)**
$\alpha^S_{Kn} \Delta_t K/(K/L)_{jt}$ [+] Acc phys capital	8.9E-09 (2.50)**	7.5E-09 (2.82)***	8.2E-09 (3.07)***	7.2E-09 (2.69)***	8.1E-09 (3.02)***	9.3E-09 (3.52)***
$(\tilde{\mu}_n \Delta \ln q_{njt})$ [?] Growth of M-size	3.6E-09 (2.18)**	2.5E-09 (3.22)***	2.4E-09 (3.09)***	2.6E-09 (3.37)***	2.4E-09 (3.09)***	2.4E-09 (3.13)***
$(R\&D/VA)_{njt}$ [+] Inv ratio in R&D	0.0013 (1.86)*	4.4E-04 (1.63)				
$(S/VA)_{njt}$ [+] R&D stock /VA			2.1E-04 (2.58)***		2.4E-04 (2.62)***	2.7E-04 (3.27)***
$(S)_{njt}$ [+] Industry R&D stock				5.1E-13 (0.52)	-7.6E-13 (-0.69)	
V^{in} $(R\&D/VA)_{njt}$ [+] R&D spillovers						0.0021 (3.16)***
$\Delta_t \ln (Ex)_{jt}$ [+] Growth in Ex-rate	4.1E-04 (1.62)	3.7E-04 (1.56)	3.9E-04 (1.61)	3.7E-04 (1.51)	3.6E-04 (1.51)	4.7E-04 (2.08)**
$V^{out}\varepsilon$ [+] Common shocks		0.2364	0.2413	0.2506	0.236	0.1748
R^2	0.114	0.050	0.050	0.047	0.052	0.062
Sq. corr		0.099	0.0945	0.081	0.096	0.101
Obs	707	707	707	707	707	707
LM-test[C]. Type of interdependence p-value: error (lag)	0.002 (0.000)		0.000 (0.000)	0.002 (0.000)	0.001 (0.000)	0.005 (0.001)

Table 1. Continued

	Mod 7	Mod 8	Mod 9	Mod 10	Mod 11	Mod 12	Mod 13
Additional hypothesis ⇒	Initial human capital stock		Initial capital stock & Market size		IRS in R&D at the firm level		
Variable [E sign] (Hypothesis)	GMM-G	GMM-G	GMM-G	GMM-G	GMM-G	GMM-G	GMM-G
$(\ln \alpha_{Hn} \Delta_t \ln H_{jt})$ [+] Acc human capital		0.0056 (1.06)	0.01119 (2.48)**	0.0107 (2.38)**	0.0109 (2.44)**	0.0120 (2.68)***	0.0120 (2.67)***
$(\ln \alpha_{Hn} \ln H_{jt})$ [?] Initial hum capital	-0.0012 (-1.70)*	6.1E-04 (0.58)					
$\alpha^S_{Kn} \Delta_t (K/L)_{jt}$ [+] Acc phys capital	6.9E-09 (2.41)**	6.3E-09 (1.53)		5.4E-09 (1.58)	5.1E-09 (1.32)	7.9E-09 (2.02)**	4.0E-09 (1.21)
$\alpha^B_{Knt} / \ln w_{rjt}$ [?] Initial phys capital			0.0308 (3.81)***	0.0219 (2.22)**	0.0219 (2.19)**	0.0290 (2.87)***	0.0238 (2.44)**
$\tilde{\mu}_n \Delta \ln q_{njt}$ [?] Growth of M-size	2.5E-09 (3.22)***	3.2E-09 (2.72)***	2.4E-09 (3.05)***	2.4E-09 (3.05)***	2.4E-09 (3.09)***	2.1E-09 (2.75)***	2.4E-09 (3.20)***
$\ln(\tilde{\mu}_n q_{njt})$ [?] Initial Market size			-2.4E-04 (-0.09)	-0.0014 (-0.53)			
$(S/VA)_{njt}$ [+] R&D stock /plant	4.0E-04 (4.06)***	3.7E-04 (2.81)***	2.6E-04 (3.04)***	2.8E-04 (3.30)***	2.8E-04 (2.32)**	5.0E-06 (0.03)	-2.4E-05 (-0.16)
$\tilde{\mu}_n$ [?] Average plant size					-4.2E-11 (-0.07)	-1.4E-09 (-1.82)*	
$\tilde{\mu}_n$ $(R\&D/VA)_{njt}$ [+] IRS in R&D						2.0E-11 (3.14)***	1.3E-11 (2.50)**
V^{in} $(R\&D/VA)_{njt}$ [+] R&D spillovers	0.0023 (3.33)***	0.0020 (2.06)**	0.0023 (3.31)***	0.0023 (3.32)***	0.0023 (3.37)***	0.0022 (3.20)***	0.0023 (3.41)***
$\Delta_t \ln (Ex)_{jt}$ [+] Growth in Ex-rate	2.5E-04 (3.22)***	0.0013 (4.10)***	4.6E-04 (2.05)**	4.6E-04 (2.10)**	4.7E-04 (2.15)**	4.6E-04 (2.11)**	4.4E-04 (2.00)**
$V^{out}\varepsilon$ [+] Common shocks	0.211	0.268	0.1689	0.160	0.167	0.162	0.166
R^2	0.058	0.063	0.067	0.069	0.068	0.068	0.066
Sq. corr	0.093	0.073	0.115	0.114	0.112	0.105	0.105
Obs	707	707	707	707	707	707	707
Type of interdependence p-value: error (lag)	0.002 (0.000)	0.000 (0.000)	0.008 (0.003)	0.009 (0.003)	0.007 (0.002)	0.008 (0.002)	0.007 (0.002)

Notes: t-value within parenthesis. *, **, *** indicate significance at the 10, 5 and 1 percent significance level. Period dummies and a constant included in all models. F-test rejects country and industry dummies in all models. The OLS model is estimated using White

(1980) heteroscedasticity consistent t-statistics. ‘V’ in the spillover and interdependence variables denotes a row standardised I/O matrix.

[A] Expected sign on the regression variables, the case of an ambiguous sign is denoted ‘?’.

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

[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 interdependence.

Market size effects

Concentration and localisation of industries is a subject that has recently received a great deal of attention from economists. This is largely due to what has become known as the new economic geography[30]. A central prediction is that decreasing trade costs will cause industries with economies of scale to become increasingly concentrated in large markets. However, as the integration process proceeds and transportation costs become small, this concentration process eventually reverses itself.[31]

In the regressions we use two interaction variables to account for this effect, obtained by multiplying a proxy for the degree of IRS, $\tilde{\mu}_n$ in an industry with (a) the initial home market size measured as industry value added, $(VA)_{njt}$ and (b), the growth rate of home market size, $\Delta_t \ln(VA)_{njt}$.

The growth rate of the markets size, $(\tilde{\mu}_n \Delta_t \times \ln(VA)_{njt})$, is found to have a significant positive impact on the evolution of the coefficient of specialisation. The interpretation is that, when an IRS industry active in a country significantly increases its output, it does so because, on average, net exports have grown faster than domestic demand. This may be seen as an outcome of industrial reallocation.

The absolute size of a market, $\tilde{\mu}_n \ln(VA)_{njt}$ never enters with a positive significant estimate (it is negative insignificant). This indicates that we do not have an increased specialisation of IRS industries in countries with large markets.[32]

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

[31] For example, decreasing returns to scale in the agriculture sector or many factors of production may reverse the concentration of industries as trade costs become small (see Fujita et al, 1999).

[32] In regressions not presented here, by interacting industries degree of IRS with countries K/L ratio, we tested if IRS industries has become increasingly concentrated in

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 brief, we find no evidence of an increased specialisation of IRS industries in countries with large markets, while countries with industries that grow relatively much have increased their specialisation in IRS industries, indicating a reallocation of industrial activity that is not systematically related to the size of countries' markets.

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 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 leads to an improvement of 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 1-7, we find support for accumulation of physical capital to shift the industry towards increased net export of capital-intensive goods. In regression models 10-13, we control for the initial price of capital when estimating the impact of capital accumulation on specialisation and find the accumulation of capital to be insignificant at the five per cent level in one out of four regressions[33]. The reduced significance in the capital accumulation variable might be driven by a

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capital-abundant countries. Regression revealed a positive but insignificant impact of this variable on the change in specialisation indicating no significant concentration of IRS industries in capital-abundant countries.

[33] 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.

positive correlation between these variables (the correlation is 0.52, which is a relatively high value).

In other studies Gustavsson *et al* (1997) found little support that accumulation of capital affected the coefficient of specialisation. Harrigan (1997) found no robust evidence that capital explained 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 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 their comparative advantage[34]. In this case, initial endowments alone would be an important determinant of future changes in trade patterns. In regression models 9-13 we append countries' (the inverse of) initial price of physical capital (interacted with industries' capital intensity) as a predictor of subsequent changes in the coefficient of specialisation. This turns out to be a significant predictor of subsequent changes in the coefficient of specialisation[35]. In regression models 10-13, *both* the accumulation of capital and its initial price are applied. As shown above this weakens the significance of the rate of capital accumulation while the initial capital price remains a significant predictor of subsequent changes in the coefficient of specialisation.

The correlation between the change in countries' capital stock per capita and its initial value is 0.33 and regressing countries' change in capital per capita on initial values verifies that capital abundant countries on average has increased their K/L ratio more than capital deficient countries.[36] It should also be noted that the correlation between countries capital abundance and the average return to capital corr(1/r, K/L) = 0.697 indicating that in capital abundant countries the average return to 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

[34] 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.

[35] For initial values, 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).

[36] In the regression, as regressors we use initial capital abundance, period dummies and a constant.

export of capital-intensive goods. This increased concentration of *capital-intensive* industries into capital-abundant countries may be seen as a market integration effect and an accommodation of countries toward their comparative advantage. It should however be noted that the correlation between the growth rate of countries capital to labour ratio and initial position is negative (-0.21), indicating a convergence in the European countries capital to labour ratio, i.e. absolute divergence but relative convergence.

Amiti (1999) provides 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[37].

Human capital

Human capital and its importance for productivity growth are stressed in the endogenous growth literature.[38] 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 in (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 (average years of schooling pop > 25 years old) tend to increase their specialisation in human capital-intensive industries.

If we apply initial levels of human capital without controlling for the rate of human capital accumulation, the estimated parameter is negative and significant at the ten percent level.[39] The interpretation is that there is a tendency for human capital-abundant countries to loose their edge in skilled intensive industries. However, the significance of both the accumulation rate and initial level of human capital disappears if we apply both variables simultaneously. This loss of significance might be driven by

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[37] 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.

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

[39] It should be mentioned that the negative significance is rather fragile with respect to model formulation. A negative but insignificant estimate is often detected in other model formulations.

a negative correlation between initial levels of human capital and the accumulation rate of human capital, in fact the correlation is found to be –0.18 (p-value 0.00). This negative relation (convergence) is verified when regressing the growth rate in human capital stock on initial human capital abundance and period dummies.[40] This means that there is a tendency for human capital deficient countries to catch up on human capital-abundant countries. However, in absolute changes the correlation between the change and initial level is basically zero, [corr($\Delta_t$edu, edu) = 0.004]. That is, for the average years of schooling we have relative convergence among the EU countries but in absolute terms the distribution is constant. Performing growth regressions using countries share of population (more than 25 years old) with post secondary education we find convergence no matter if we use growth rates or changes as dependent variable (regressions available on request). That is, we find accumulation of human capital to affect specialization patterns and human capital deficient EU countries have increased their supply of skilled labour more than human capital abundant EU countries.

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 fluctuations 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 per cent level in eight out of thirteen models, with estimated parameters running from 0.00025 to 0.0013. That is, a depreciation of 10% relatively to the USD in a five year period is expected to increase the growth in the coefficient of specialisation by 0.0025-0.013 percentage points.

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[41]. 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*?

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[40] Regressions are available on request.

[41] See, for example Aghion (1992), Romer (1990) or Young (1998) for a model without scale effects, and a discussion.

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 cases where all firms in an industry 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 and 2, the industry R&D intensity ($R\&D/VA)_{njt}$, is used as a regressor. According to the OLS estimate in regression model 1, a ten percentage unit 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 0.013 percentage units.[42]

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

In model four and five industry-specific $(S)_{njt,}$, R&D stocks are applied. These *never* generate a positive and significant impact on growth in the coefficient of specialisation, no matter how the regressions are specified. In regressions not presented here national R&D stocks were also used. These also failed to generate a significant impact on growth in the coefficient.[43] These results are consistent with the hypothesis that what matters for 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 proxied 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.

If we have scale effects in R&D at the firm level, large firms will have an edge over small firms. In regression models 11-13, we investigate scale effects in R&D at the firm level. In regression model 11, the variables plant size, $\tilde{\mu}_n$, and R&D, $(S/VA)_{njt}$ are applied.[44] We find no significant plant-size effects while the effect of R&D is both positive and significant. In regression model 12, the interaction effect between R&D and plant size,

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[42] To reduce noise and lag sensitivity a three-year, lagged average is used. See Appendix 2 for details.

[43] Regressions available on request.

[44] Due to 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.

$\tilde{\mu}_n \times (S/VA)_{njt}$, is appended. The interaction variable is positive and strongly significant while the effect of a firm's own R&D and plant size becomes insignificant.[45] The interaction term overtakes the effect of R&D. The significance of the interaction term remains, even if we drop the firm size variable. 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. Technical progress in one industry may not only be driven by its own R&D, but also by R&D in other domestic 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. This is consistent with viewing trade as a carrier of technology transfers and in line with Keller (1997) and Coe & Helpman (1995), for example[46].

In regression models 6-13, the input-weighted R&D intensities in other domestic industries [$V^{in}(R\&D/VA)_{njt}$][47] are 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%.

The results indicate *small domestic inter-industry technology 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 firms with large R&D departments generating new technology and technology transfers. Thus the disadvantage

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[45] In this specification the effect of plant size turns out to be negatively significant at the five per cent level. However, in other specifications, this variable is mostly negative and insignificant.

[46] Coe and Helpman, however, study cross-country technology transfers.

[47] The main diagonal of the weight matrix, V, is set to zero since we want to exclude the impact of own R&D.

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.

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?[48] This question may be answered by means of spatial econometric techniques where we replace the usual distance measure with I/O coefficients.

If industries are exposed to common shocks, this will result in an interdependent error term[49]. 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[50].

The econometric results strongly support the hypothesis that domestic industries experience common shocks. The estimated coefficient is in the interval 0.16-0.27. The interpretation of a coefficient of 0.20 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 $0.20\times\lambda$ units.[51] 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, ($V^{out}\times\Delta_t\, r$), and estimate the model by means of 3SLS. A generalised model is then $y = \rho Wy + xB + \eta$ where y is the dependent

[48] Through this, we relax the usual econometric independence assumption.

[49] 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 inter-dependence is in the dependent variable and not controlled for, this generates an omitted variable bias.

[50] 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).

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

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 using IV-techniques is roughly in the range 0.9-1.2 and 0.35-0.45 when using ML estimators. The estimated interdependency coefficient is 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 rate variable and some of the other independent variables turn from being significant to insignificant when the interdependency is modelled in the independent variable and IV-techniques are used. This may been seen as an effect of reduced efficiency when using IV techniques. There is, however, robust evidence for interdependent industries.[52]

Other variables

A set of other H-O variables, not presented in Table 1, was tested. 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, 1999), these variables were found to be important determinants of the level of specialisation. These endowments do not change by much over time and do not add much to explanations of changes in trade patterns.

5. Conclusions

In this paper we analyse changes in countries' specialisation patterns using a trade model that embeds factor prices, technology, and scale effects. Using a technological quality ladder, industries' technological progress - driven by R&D- and domestic inter-industry technological transfers are made endogenous.

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[52] The efficiency properties of the IV estimations and the non-bounded parameter estimate of interdependence when using IV techniques make the GMM estimations preferred.

Empirically we study 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 studies how changes in specialisation are related to countries' accumulation rate of productive factors, technology, initial factor abundances (in levels) and market size effects.

We find that a countries that *increases its capital to labour ratio* relatively much turns the industry toward increased net export in capital-intensive industries. This might partly be seen as a shift in the age composition of the capital stock 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 increased their capital to labour ratio most. This is an indication of an ongoing concentration of capital-intensive industries into capital-abundant countries.

For human capital, we find 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 in human capital abundant countries; rather, there is convergence in that we find human capital deficient countries to have the highest accumulation rates of human capital.

Analysing the impact of R&D on competitiveness, we find a positive and significant impact of R&D on specialisation. 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 may reflect the amount of resources allocated to R&D by the representative firm. There is no evidence whatsoever that the absolute size of industries or countries' R&D stocks to have any impact on competitiveness and changes in specialisation. We may take this as an indication that R&D at the firm level is what matters for productivity growth and increased competitiveness, hence there is no evidence of an R&D disadvantage for firms located in small markets.

Investigating scale effects in R&D at the firm level, we interact a proxy for firms' R&D effort with industries' average firm 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 [(Industry R&D per value added)×(firm size)], controlling for the effects of the firms' own R&D and firm size.

National inter-industry technology transfers are analysed using national I/O tables as a weighting matrix. Positive and robust significant inbound R&D transfers are detected when applying industries' investment ratios in R&D. No technology transfers are found from the pure size of industries' R&D stocks. In line with Keller (1997), the relatively small coefficient on technology spillovers (roughly around 0.2%) emphasises that firms' own R&D is much more important for competitiveness than R&D performed in other domestic industries.

The econometric analysis gives no support for a concentration of IRS industries in countries with large markets, while for IRS industries that increase their output, net export has on average increased faster than domestic consumption.

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 domestic industries that trade a lot with each other are 'close to each other' and hit by common shocks that make 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 via I/O links. The strength of the estimated interdependence lies in the interval 16-26%. Hence, the traditional route of treating industries as independent may be misleading.

Exchange rate fluctuations are found to affect trade patterns in that a depreciation of the currency, as expected, boosts growth in the coefficient of specialisation. The significance of this effect increases as we append more control variables to the model.

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% and 9-11%, respectively. This might appear to be a bit disappointing since level studies often have an R^2 of 40-70 per cent (sometimes even higher). However, one should keep in mind that fixed effects, which are differenced out here, drive much of the R^2 in level studies. On the other hand, analysing changes allows us to make a simultaneous analysis of accumulation effects and potential level dependence. To sum up, we found that domestic industries are interdependent, there is 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 the following, we build upon the model 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 yield, 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, measured 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_{nj2}^{ss} 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*.

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

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 now convenient to let *z* denote the state of technology and *i* the generation of innovation in the industry. The expected step size in innovations in other industries for an intermediate good producer in industry *n* during the patent time equals

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

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 the profit we may 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

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

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

where $(i+1)_0^I$ 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:

$$1 = \lambda\frac{\sigma_n(1-\alpha_{xn}) + \alpha_{xn}}{\alpha_{xn}(\sigma_n - 1)}\gamma^{\tilde{\alpha}_{nj}\tilde{Z}_{nj}}$$
$$\times\frac{e^{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss}) - r]T}}{[\lambda(\tilde{H}_{j2}^{ss}\tilde{\alpha}_{nj}\ln\gamma - H_{nj2}^{ss}) - r]}(H_{nj}^{ss} - H_{nj2}^{ss}). \tag{A1.10}$$

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*] ⇒$dt = 1/\lambda H_{nj2}$ or equivalently di/dt = λH_{nj2}. Integrating both sides gives $i(t) = \lambda H_{nj2}t$. Substitution of *i* gives $A(i)_{nj} = A(0)_{nj}e^{\ln\gamma\alpha_{xn}\lambda H_{nj2}^{ss}t}$. The growth rate is then easily found, as stated in Eq. (9). For the extended model, a similar approach is used.

Appendix 2

Data, Variables and Time

Data for most country-specific variables are annual observations spanning 1976-96. Due to availability of cross-country educational data, the regression variables are based on changes over five years. The years used are: 1976, 1981, 1986, 1991 and 1996, resulting in four time periods. In order to downplay the impact of outliers and missing values, most variables are taken as averages over two to three years. For the independent variables, an impact lag of one to two years is imposed.

Coefficient of specialisation

$$r_{njt} = \frac{Q_{njt}}{C_{njt}} = \frac{C_{njt} + X_{njwt} - M_{nwjt}}{C_{njt}} = 1 + \frac{X_{njwt} - M_{nwjt}}{C_{njt}}$$

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).

C_{nwjt} Consumption, goods classified to industry *n*, country *j*, year *t*, average (*t-1*)-(*t+1*). Source: OECD (1998).

Skilled labour

$(\ln\alpha_{Hn} \times \Delta_t \ln H_{jt}$ and $\ln\alpha_{Hn} \times \ln H_{jt})$

α_{Hn} Cost share of human capital in value added, industry n, Sweden 1993.

$$\alpha_{Hnt} = (W_{jnt} / VA_{jnt}) \times (W_n^{s,swe} / W_n^{swe})$$

W_{jnt} Total wages sum country j, industry n, year t. Source: OECD (1998).

VA_{jnt} Value added country j, industry n, year t. Source: OECD (1998).

$W_n^{s,swe}$ Wages sum to skilled labour (with post-secondary education), industry n, Sweden 1993. Source: SCB RAMS 1993.

W_n^{swe} Total wages sum industry n, Sweden 1993. Source: SCB RAMS 1993.

H_{jt} Average years of schooling of population over 25 years.

country *j* year *t*, lagged one year. Source: Barro & Lee (2000).

Physical Capital

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

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

k_{jt} National capital stock per capita, 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, national capital stocks are used (and thus, we 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

$\ln(\tilde{\mu}_n (VA)_{njt})$ and $\tilde{\mu}_n \Delta_t \ln(VA)_{njt}$

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

$\tilde{\mu}_n \quad = 1/J \sum_{j \in J} \left(VA_{njt} / F_{njt} \right) \;;\quad t = 1989$

F_{nj} Number of establishments, industry *n*, country *j*, year 1989. Source: OECD (1995a).[53]

$(VA)_{njt}$ 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.

[53] The number of establishments is only available for a few points in time.

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.

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

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

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

$\Delta_t ln\ Ex_t$ Growth rate in the exchange rate (currency(j) / 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 the matrix is row standardised such that each row is equal to one. Due to a non-linear relation, in the applied matrices, the square root of the I/O coefficient is applied. Source: OECD (1995b)

Technology transfers

$V^{in} \times (R\&D/VA)_{njt}$

V^{in} I/O coefficient matrix for inputs from other domestic industries. The main diagonal is set to zero.

$(R\&D/VA)_{njt}$ 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, input-output table for Sweden 1985.

SCB, Regional Labour Statistics, (RAMS).

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

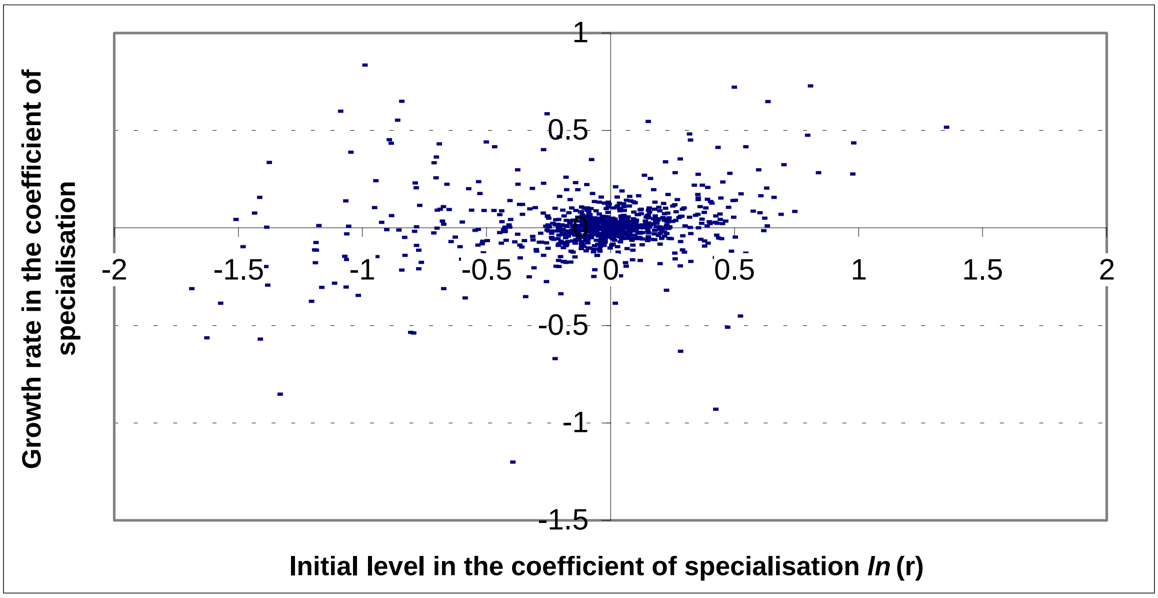

Table A3.1. Correlation Matrix.

	Dep var $\Delta_t lnr$	*H-Cap* $\alpha_{nH}\Delta_t H$	*H-Cap* $\alpha_{nH}H$	*Cap* $\alpha_{nK}\Delta_t K$	*Cap* $\alpha_{nK}K$	*Cap* α_{nK}/r	$V^{in\times}$ R&D /VA	*Tech* R&D /VA	*Tech* S/VA	*Tech* S_{njt}	IRS× R&D /VA	Δ_t *ln* ex-rate	Δ_t Msize
$\alpha_{nH}\Delta_t H$	.064	1											
$\alpha_{nH}H$	.087	.155	1										
$\alpha_{nK}\Delta_t K$	.039	.072	-.297	1									
$\alpha_{nK}K$	.099	.036	-.193	.833	1								
α_{nK}/r	.111	-.054	-.258	.519	.568	1							
$V^{in\times}$R&D/VA	.060	.065	.223	.033	.060	-.100	1						
R&D/VA	.165	.122	.471	-.139	-.143	-.021	-.129	1					
S/VA	.114	.111	.513	-.165	-.159	-.052	-.106	.707	1				
S_{njt}	-.044	-.020	.226	-.119	-.127	-.156	-.108	.128	.306	1			
IRS×R&D/VA	.073	.055	.343	-.102	-.101	-.054	-.116	.505	.720	.339	1		
Δ_t *ln*ex-rate	.087	-.259	-0.095	-0.116	-0.024	-.011	-.087	-.029	-.037	-.048	-.014	1	
Δ_t M-size	.071	.026	0.101	0.090	0.053	.092	-.044	.158	.096	-.018	.048	.032	1
M-size	-.114	-.214	-0.254	0.139	0.053	.033	-.271	-.165	-.037	.460	.144	.007	-.147

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. Countries Endowments

	K/L (rank)	Edu* (rank)
Denmark	17 (3)	9.4 (1)
Finland	21 (2)	7.9 (7)
France	15 (5)	7.3 (8)
Germany	14 (6)	9.0 (3)
Italy	12 (8)	5.8 (9)
Netherlands	13 (7)	8.3 (6)
Norway	23 (1)	8.4 (5)
Spain	8 (10)	5.3 (10)
Sweden	17 (4)	9.2 (2)
United Kingdom	9 (9)	8.4 (4)

*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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