Journal of International Economics 58 (2002) 299–334
Journal of INTERNATIONAL ECONOMICS
www.elsevier.com/locate/econbase

Specialization dynamics

Stephen Redding*

Department of Economics, London School of Economics and CEPR, Houghton Street, London WC2A 2AE, UK

Received 22 September 1999; received in revised form 27 September 2001; accepted 28 October 2001

Abstract

This paper proposes a new empirical framework for analyzing specialization dynamics. A country's pattern of specialization is viewed as a distribution across sectors, and statistical techniques for analyzing the evolution of this entire distribution are employed. The empirical framework is implemented using data on 20 industries in seven OECD countries since 1970. We find substantial mobility in patterns of specialization. Over time horizons of 5 years, this is largely explained by forces common across countries, including world prices and common changes in technical efficiency. Over longer time horizons, country-specific changes in factor endowments become more important. There is no evidence of an increase in countries' overall degree of specialization.

Keywords: Distribution dynamics; Factor endowments; International trade; Neoclassical model

JEL classification: F11; F14; C14

1. Introduction

Theoretical models of trade and growth emphasize that patterns of specialization are dynamic and evolve endogenously over time. This contrasts with much of the existing empirical trade literature, which is concerned with production and trade at a point in time. This paper proposes a new empirical framework for analyzing

*Tel.: +44-20-7955-7483; fax: +44-20-7831-1840.
E-mail addresses: s.j.redding@lse.ac.uk (S. Redding), http://econ.lse.ac.uk/~sredding/ (S. Redding).

0022-1996/02/$ – see front matter
PII: S0022-1996(01)00169-6

specialization dynamics. The analysis begins with a measure of a country's extent of specialization in an individual industry derived directly from neoclassical trade theory: the share of the industry in that country's GDP. A country's pattern of specialization at any one point in time is characterized by the distribution of shares of GDP across industries. The dynamics of a country's pattern of specialization correspond to the evolution of this *entire* cross-section distribution over time. The focus on a country's distribution of GDP shares across industries means that the paper is concerned with production structure within countries. We employ a statistical model of distribution dynamics that has been widely used in the cross-country growth literature and is explicitly suited to analyzing the evolution of entire distributions. The empirical framework is implemented using data on 20 industries in seven OECD countries since 1970.[1]

Using these techniques, it becomes possible to analyze a variety of issues relating to specialization dynamics that are suggested by the theoretical literature on trade and growth. One set of issues relates to the evolution of the *external shape* of the distribution of GDP shares and concerns changes in countries' overall degree of specialization—the extent to which production activity is concentrated in a few industries. For example, more rapid technological progress in the industries in which a country specializes and the accumulation of factors used intensively in these industries will result in increased specialization over time. This will be reflected in a polarization of the distribution of GDP shares towards extreme values, as countries increasingly specialize in one set of industries and reduce specialization in others. In the extreme, a bimodal or ''twin-peaked'' distribution will emerge.

A second set of issues relates to how a country's extent of specialization in individual industries changes over time and is concerned with *intra-distribution dynamics*. A number of theoretical models of trade and growth identify reasons why initial patterns of specialization may either be locked-in (*persistence*) or reversed (*mobility*) over time. Whether patterns of specialization exhibit persistence or mobility therefore becomes an empirical question which can be addressed by analyzing the movement of industries within a country's distribution of GDP shares. Suppose an industry lies in the lower tail of the distribution of GDP shares. What is the probability over a given period of time that the industry will remain there? What is the probability that it will transit to the upper tail of the distribution of GDP shares and become a sector in which the country specializes? Where in the distribution is the greatest degree of mobility observed?

A third set of issues concerns the economic determinants of changes in a distribution's external shape and of industries' movements within the distribution of GDP shares. A structural econometric equation linking GDP shares, relative

[1] Rather than focusing on production structure within countries, one could also use the same techniques to analyze the evolution of the distribution of production activity across countries within an industry. This is closely related to the concept of localization in the empirical economic geography literature (see, for example, Overman et al., 2001).

prices, technology levels, and factor endowments is derived from neoclassical trade theory. This econometric relationship is used to decompose observed changes in patterns of specialization into two components: (a) country-specific changes in factor endowments and (b) forces which are either common across countries but specific to individual industries (e.g. changes in industry prices on world markets, pervasive changes in technical efficiency in individual industries) or common across both countries and industries (e.g. shared changes in technical efficiency across all manufacturing industries, common changes in factor endowments across all countries). The same model of distribution dynamics may be used to analyze how patterns of specialization—the entire distribution of GDP shares—would have evolved if only country-specific changes in factor endowments had occurred or if only common forces across countries had operated.

Our main findings are as follows. First, there is substantial mobility in patterns of specialization. In the United States, the probability of an industry transiting out of its initial quintile of the distribution of GDP shares after 5 years varies from 0.39 towards the centre of the distribution to around 0.20 in the upper and lower tails. The highest levels of mobility are found in Japan and Sweden; Canada, the United Kingdom, and United States have intermediate levels; Denmark and Finland display the least.

Second, we find no evidence of an increase in the extent to which countries' production is concentrated in a few industries. Indeed, in Finland and Denmark, there is an increase in the number of industries located at intermediate values for shares of GDP, suggesting a decrease in specialization in these countries. Third, estimation of the structural econometric equation derived from neoclassical theory reveals factor endowments to be an important determinant of patterns of specialization. Over time horizons of 5 years, country-specific changes in factor endowments are found to be less quantitatively important in explaining the observed mobility in specialization patterns than forces which are common across countries. Exceptions are Japan and Finland, where changes in factor endowments explain the majority of the observed mobility even over 5-year periods. In Japan, this is related to a combination of rapid physical capital accumulation and skill acquisition; in Finland, skill acquisition plays a central role.

Over longer time horizons of 10 years and above, common cross-country effects remain influential, but country-specific changes in factor endowments become relatively more important. In the literature on international trade and wage inequality, there is considerable debate concerning the speed at which ''the Heckscher–Ohlin clock ticks''.[2] In another context, our findings suggest that it takes time for gradual changes in countries' relative factor abundance to manifest themselves in substantial changes in production structure.

The paper is organized as follows. Section 2 reviews the relationship to the existing literature. Section 3 derives a measure of a country's extent of specializa-

[2]See, for example, the discussion in Leamer (1998).

tion in individual industries directly from neoclassical trade theory and obtains a structural econometric equation linking this measure to factor endowments, relative prices, and technology. Section 4 introduces a model of distribution dynamics which, given this measure, may be used to analyze the dynamics of a country's pattern of specialization. Section 5 undertakes a preliminary analysis of the data. Section 6 presents the results of the econometric estimation. Section 7 concludes.

2. Relation to existing literature

The paper is related to three main bodies of existing work. First, the theoretical literature on trade and growth provides motivation. One strand of this literature emphasizes the role of endogenous technological change. In the absence of international knowledge spillovers, models of endogenous investments in R&D or sector-specific learning by doing predict that initial patterns of specialization will become locked-in over time (e.g. Krugman, 1987; Lucas, 1988; Grossman and Helpman, 1991, Chapter 7; Redding, 1999a). However, both international knowledge spillovers and cross-country differences in the productivity of R&D/rates of learning by doing provide reasons why initial patterns of specialization may be reversed over time (e.g. Grossman and Helpman, 1991).

Another strand of theoretical research emphasizes the role of factor accumulation (including Findlay, 1970; Deardorff, 1974; Davis and Reeve, 1997). Again, initial patterns of specialization may be reinforced or weakened over time. The point is made particularly clearly in the $2 \times 2 \times 2$ Heckscher–Ohlin model, where this depends simply upon whether the initially capital-abundant or capital-scare country experiences the more rapid rate of increase in its endowment of capital relative to labour. If the former, then not only will initial patterns of specialization become locked-in, but countries' overall degree of specialization will rise over time.

Second, the paper relates to the empirical literature that estimates the relationship between factor endowments and the international location of production. Harrigan (1995) and Bernstein and Weinstein (1998) regress output levels on factor endowments in a specification derived directly from the n-good, m-factor Heckscher–Ohlin model. Factor endowments are found to have a statistically significant and quantitatively important effect on levels of production, although within-sample predictions errors are typically large, particularly using regional data.[3]

[3] See Hanson and Slaughter (1999) and Gandal et al. (2000) for analyses of the generalized Rybczynski Theorem using US State and Israeli data. Another literature considers the relationship between factor endowments and international trade in factor services. See, for example, Leamer (1984), Bowen et al. (1987), Trefler (1995), and Davis et al. (1997).

Harrigan (1997) estimates the neoclassical model of production and finds that levels of technology as well as factor endowments are important determinants of patterns of specialization. Harrigan and Zakrajsek (2000) estimate the model for a broad sample of developed and developing countries and find that factor endowments are a major influence on specialization.[4] With the exception of Harrigan (1997), each of these papers is concerned with a static relationship between factor endowments and production patterns at a point in time. Harrigan (1997) also considers a dynamic specification where a regression of GDP shares on factor endowments, technology levels, and controls for relative prices is augmented with a lagged dependent variable. This specification allows for partial adjustment, and the coefficient on the lagged dependent variable is found to be highly statistically significant. However, there is no analysis of the implications for intra-distribution dynamics or the evolution of the external shape of the distribution of GDP shares.

Third, a small number of papers have explicitly considered changing patterns of trade and production. One older branch of research has addressed these issues within the context of the $n \times m$ Heckscher–Ohlin model. This includes Balassa (1979), Stern and Maskus (1981), Bowen (1983), and Maskus (1983). While the first two studies consider cross-*country* regressions of RCA and net exports on factor endowments, the last two analyze cross-*industry* regressions of net exports on factor endowments for a single country (the United States).[5] The relative availability of skilled and unskilled labour is typically found to be an important determinant of patterns of comparative advantage, and US-based studies find that by the 1970s the Leontief Paradox no longer held.

An alternative branch of research has adopted a more descriptive approach less directly linked to theory. Kim (1995) and Amiti (1999) analyze a production-based measure of specialization (the ''location quotient'') that is directly analogous to trade-based measures of Revealed Comparative Advantage (RCA).[6] Both papers examine changes in countries' overall degree of specialization using summary statistics such as the coefficient of variation or Gini coefficient. While informative, these are not generally sufficient statistics for a distribution's external shape and yield no information concerning intra-distribution dynamics.

Proudman and Redding (1998, 2000) use a *RCA*-based measure of specialization to analyze both persistence versus mobility and changes in countries' overall degree of specialization. A model of distribution dynamics is used to analyze the

[4] See Nickell et al. (2001) for a neoclassical analysis of OECD countries' specialization in non-manufacturing industries.

[5] See Feenstra and Rose (2000) for an analysis of the dynamic predictions of the product lifecycle hypothesis for cross-country export patterns.

[6] Revealed Comparative Advantage (RCA) is defined as a country's share of world exports in sector j divided by that country's share of world exports of all goods. The ''location quotient'' is thus a country's share of world production in sector j divided by the country's share of world production of all goods.

evolution of the entire distribution. However, the measure of specialization used is ad hoc and cannot easily be related to general equilibrium trade theory. For these reasons, it is not possible to link changes in specialization patterns to structural economic determinants.[7]

3. Neoclassical theory and economic determinants

In this section, we use neoclassical trade theory to derive a theory-consistent measure of specialization and to relate that measure to underlying structural economic determinants (see Dixit and Norman, 1980, for a wider exposition). Time is indexed by t, countries by $c \in \{1, \ldots, C\}$, final goods by $j \in \{1, \ldots, n\}$, and factors of production by $i \in \{1, \ldots, m\}$. Each country is endowed with an exogenous vector v_{ct} of factors of production, and production is assumed to occur under conditions of perfect competition and constant returns to scale. We allow for differences in factor endowments across countries c and technology differences across both countries c and industries j.

General equilibrium in production may be represented using the revenue function $r_c(p_{ct}, v_{ct})$. Under the assumption that this function is twice continuously differentiable, the vector of the economy's profit-maximizing net outputs $y_c(p_{ct}, v_{ct})$ is equal to the gradient of $r_c(p_{ct}, v_{ct})$ with respect to p_{ct}.[8] The analysis allows for Hicks-neutral and factor-augmenting technology differences. Our main specification considers Hicks-neutral technology differences across countries, industries, and time. In this case, the production technology takes the form $y_{cjt} = \theta_{cjt} F_j(v_{cjt})$, where θ_{cjt} parameterizes technology in industry j of country c at time t. The revenue function is given by $r_c(p_{ct}, v_{ct}) = r(\theta_{ct} p_{ct}, v_{ct})$, where θ_{ct} is an $n \times n$ diagonal matrix of the technology parameters θ_{cjt}.[9] Changes in technology in industry j of country c have analogous effects on revenue to changes in industry j prices.

We follow Harrigan (1997) and Kohli (1991) in assuming a translog revenue function. This flexible functional form provides an arbitrarily close local approximation to the true underlying revenue function,[10]

[7] For related work, again using ad hoc and atheoretic measures of specialization such as RCA or the location quotient, see Brasili et al. (1999), Hinloopen and van Marrewijk (1998), and Stolpe (1994).

[8] Formally, a sufficient condition for the revenue function to be twice continuously differentiable is that there are at least as many factors as goods: $m \geq n$. With $n > m$, production levels may be indeterminant, although this will depend on technology differences, trade costs, and whether or not there is joint production. The potential existence of production indeterminacy is really an empirical issue. In the presence of production indeterminacy, the specification below including factor endowments and controls for relative prices and technology will be relatively unsuccessful in explaining countries' patterns of production.

[9] See Dixit and Norman (1980, pp. 137–139).

[10] To save notation, country–time subscripts are suppressed except where important.

$$\ln r(\theta p,v) = \alpha_{00} + \sum_j \alpha_{0j} \ln \theta_j p_j + \tfrac{1}{2}\sum_j \sum_z \alpha_{jz} \ln(\theta_j p_j) \ln(\theta_z p_z)$$
$$+ \sum_i \beta_{0i} \ln v_i + \tfrac{1}{2}\sum_i \sum_h \beta_{ih} \ln v_i \ln v_h + \sum_j \sum_i \gamma_{ji} \ln(\theta_j p_j)(\ln v_i), \quad (1)$$

where $j,z \in \{1, \ldots, n\}$ index goods and $i,h \in \{1, \ldots, m\}$ index factors. Symmetry of cross effects implies: $\alpha_{jz} = \alpha_{zj}$, $\beta_{ih} = \beta_{hi}$ for all j, z, i, and h. Linear homogeneity of degree 1 in v and p requires: $\Sigma_j \alpha_{0j} = 1$, $\Sigma_i \beta_{0i} = 1$, $\Sigma_j \alpha_{zj} = 0$, $\Sigma_i \beta_{ih} = 0$, $\Sigma_i \gamma_{ji} = 0$. Differentiating the revenue function with respect to each p_j, we obtain the following equation for the share of industry j in country c's GDP at time t:

$$s_{cjt} = \frac{p_{cjt} y_{cjt}(\theta_{ct} p_{ct}, v_{ct})}{r(\theta_{ct} p_{ct}, v_{ct})} = \alpha_{0j} + \sum_z \alpha_{jz} \ln p_{czt} + \sum_z \alpha_{jz} \ln \theta_{czt} + \sum_i \gamma_{ji} \ln v_{cit}. \quad (2)$$

This equation provides the theory-consistent measure of specialization in an industry (the share of the industry in the country's GDP) that will be used with the model of distribution dynamics introduced below. It also relates the specialization measure to underlying economic determinants: relative prices, technology, and factor endowments. The translog specification implies coefficients on these variables that are constant across countries and over time. This is true even without factor price equalization. Indeed, with cross-country differences in technology, factor price equalization will typically not be observed. The effect of cross-country differences in relative prices and technology on patterns of production is directly controlled for by the presence of the second and third terms on the right-hand side of Eq. (2). The analysis so far makes no assumptions about whether countries are large or small and allows for both tradeable and non-tradeable goods. If countries are small and all goods are tradeable, the vector of relative prices will be determined exogenously on world markets. With either large countries or non-tradeable goods, relative prices will be endogenous and will depend in part on factor endowments. Other things equal and on average across industries in a given country, the relative price of a non-traded good will be lower the more intensively it uses the country's relatively abundant factors of production.

If all goods are freely traded, relative prices will be the same across countries ($p_{czt} = p_{zt}$ for all c), and the second term on the right-hand side of Eq. (2) can be captured by a full set of time dummies for each industry j. In practice, there may be country-specific barriers to trade and some goods may be non-tradeable, and we wish to allow for both possibilities. We therefore follow Harrigan (1997) in modelling non-traded goods prices as being drawn from an estimable probability distribution, consisting of a country–industry effect, industry-time dummies, and an independently distributed stochastic error.

The specification in (2) is more general than those typically considered in the empirical trade literature, and allows for cross-country differences in technology, the magnitude of which may vary across industries as is consistent with empirical evidence.[11] In principle, the Hicks-neutral technology differences, θ_{cjt}, can be measured using data on factor inputs and output together with results from the literature on Total Factor Productivity (TFP) measurement (see, for example, Caves et al., 1982; Harrigan, 1997). However, compatible data on factor inputs and outputs are not available at the level of the highly disaggregated manufacturing industries considered in this paper. We therefore also model country–industry technology differences as being drawn from an estimable probability distribution.[12] From (2), our main estimation equation becomes

$$s_{cjt} = \eta_{cj} + f_{jt} + \sum_i \gamma_{ji} \ln v_{cit} + \omega_{cjt}, \tag{3}$$

where the country–industry effect, η_{cj}, controls for any permanent country–industry–specific barriers to trade and/or any permanent country–industry differences in technology. The industry–year dummies, f_{jt}, capture common changes in relative prices across countries in individual industries, common and potentially industry-specific changes in technology, and common changes in factor endowments across all countries.

Eq. (3) may be estimated separately for each industry using a panel of data across countries and over time. Observed changes in countries' patterns of specialization are explained by a combination of country-specific changes in factor endowments, v_{ct}, and forces which are common across countries and potentially industry-specific, f_{jt}. If one country accumulates a given factor of production over time, this will result in changes in industrial structure. On average, industries using this factor of production the most intensively will experience the greatest increases in output, while those using the factor of production least intensively will experience the smallest increases in output. This will have implications for both the location of individual industries within the distribution of GDP shares and for the external shape of this distribution. If the factor of production accumulated is used most intensively in the industries where the country is initially specialized, we will observe persistence in initial patterns of specialization over time and an increase in the country's overall degree of specialization. These specialization dynamics correspond to movements between long-run equilibria. The model of distribution dynamics may also be applied to the predicted values for shares of GDP from Eq. (3). We denote these by s^{P}_{cjt}:

$$s^{\mathrm{P}}_{cjt} = \hat{\eta}_{cj} + \hat{f}_{jt} + \sum_i \hat{\gamma}_{ji} \ln v_{cit}, \tag{4}$$

[11] See, for example, Harrigan (1997, 1999), and Griffith et al. (2000).

[12] An alternative would be to aggregate up to a higher level of industrial disaggregation. However, this would entail losing a wide range of interesting specialization dynamics.

where a hat above a parameter denotes an estimated value. Comparing the results of the distribution dynamics analysis with those using actual shares of GDP reveals the extent to which the model is able to explain observed changes in specialization patterns—both changes in external shape and movements of individual industries within the distribution of GDP shares.[13]

Eq. (3) may also be used to decompose observed changes in specialization into the component explained by common cross-country effects and the component explained by factor endowments. Predicted values may be constructed holding factor endowments constant at their beginning of sample values, v_{c0}, and only allowing the industry–year effects, f_{jt}, to change over time. We denote these by s^{I}_{cjt} (industry–year predictions). Similarly, predicted values may be constructed holding the industry–year effects constant at their beginning of sample values, f_{j0}, and only allowing factor endowments, v_{ct}, to change over time. We denote these by s^{E}_{cjt} (endowment predictions). Applying the model of distribution dynamics to s^{I}_{cjt} and s^{E}_{cjt} reveals the extent to which common cross-country effects and country-specific changes in factor endowments, respectively, can explain observed specialization dynamics.

The error in Eq. (3) includes stochastic determinants of relative prices and technology not captured by a country–industry effect and industry-time dummies. If these are uncorrelated with factor endowments, estimation of Eq. (3) will yield unbiased and consistent values of the structural parameters γ_{ji}. These correspond to the *Rybczynski derivatives* of Heckscher–Ohlin theory: the *direct* general equilibrium effects of changes in factor endowments on the shares of sectors in GDP, holding constant relative prices and technology. More generally, the estimated coefficients on factor endowments will also capture the effects of stochastic determinants of relative prices and technology correlated with factor endowments (to the extent that these are not controlled for by the country–industry effect and industry–time dummies). If countries are large or goods non-tradeable, changes in factor endowments will affect relative goods prices, giving rise to a correlation between endowments and relative prices. In the absence of factor price equalization, relative factor abundance may influence the direction of technological change. Entrepreneurs may endogenously choose innovative effort in response to factor intensities and relative factor prices, inducing a correlation between endowments and technology.[14]

In each case, the correlation is capturing an *indirect effect* of factor endowments on output levels—in the first case through relative prices and in the second through technology levels. In the distribution dynamics analysis, we are not concerned with the structural estimation of Rybczynski derivatives. Rather, we seek to examine how much of the observed changes in patterns of specialization can be statistically

[13]For a related analysis of conditioning in distribution dynamics models of growth, see Quah (1996b, 1997).

[14]See Acemoglu (1998) for an analysis of directed technological change and wage inequality.

explained by country-specific changes in factor endowments and by considerations that are common across countries. For this purpose, it does not matter whether the coefficient on factor endowments is capturing a direct Rybczynski effect or an indirect effect through relative prices and technology. The analysis simply examines how patterns of specialization are predicted to evolve based on factor endowments on the one hand and considerations that are common across countries and potentially industry-specific on the other hand.

The industry–time dummies impact on patterns of specialization because their value typically varies across industries. Changes in relative prices will, for example, lead some industries to expand and others to contract, resulting in both intra-distribution dynamics and changes in external shape. Although the industry–time dummies in Eq. (3) take the same value for all countries, their effect on patterns of specialization will be different in different countries. This is because the effect on patterns of specialization depends on the correlation between common changes in industry size on the one hand and a country's *initial* pattern of specialization on the other. For example, suppose that all countries experience a systematic increase over time in the GDP share of Chemicals and a systematic decrease in the GDP share of Iron and Steel. For those countries that initially specialize in Chemicals and where Iron and Steel is initially a small share of GDP, this common change in industrial structure will result in an increased degree of specialization and a polarization of GDP shares towards extreme values. For those countries that initially specialize in Iron and Steel and where Chemicals is initially a small share of GDP, a decrease in the extent of specialization and mobility within the distribution of GDP shares will be observed.

The evolution of countries' patterns of specialization will also vary substantially depending upon their precise paths of factor accumulation and the correlation between factor accumulation and the factor intensities of industries where they initially specialize. For these reasons, the model of distribution dynamics introduced in the next section is estimated country by country.

4. Empirical modelling of specialization dynamics

Denote a country c's extent of specialization in industry j at time t by s_{cjt}. A country's pattern of specialization at a point in time is characterized by the cumulative distribution function of s_{cjt} across industries j, $F_{ct}(s)$. Corresponding to F_{ct}, we may define a probability measure, λ_{ct},

$$\lambda_{ct}((-\infty,s]) = F_{ct}(s), \quad \forall s \in \Re\,, \tag{5}$$

where, in the empirical application below, s_{cjt} is the share of an industry in a country's GDP and λ_{ct} is the probability density function for shares of GDP across industries j in country c at time t.

The dynamics of a country's pattern of specialization correspond to the evolution of the entire cross-section distribution of s over time. We employ a statistical model of distribution dynamics that has been widely used in the cross-country growth literature. Following Quah (1993, 1996a,b) the evolution of the cross-section distribution is modelled using a stochastic difference equation:

$$\lambda_{ct} = P_c^*(\lambda_{c(t-1)}, u_t), \text{ integer } t, \tag{6}$$

where $\{u_t : \text{integer } t\}$ is a sequence of disturbances to the entire distribution and P_c^* is an operator that maps disturbances and probability measures into probability measures. For simplicity, we begin by assuming that this stochastic difference equation is–first order and that the operator P_c^* is time invariant. Absorbing the disturbance u_t into the definition of the operator P_c^*, we obtain

$$\begin{aligned} \lambda_{c(t+\tau)} = P_c^*(\lambda_{c(t+\tau-1)}) \quad &= P_c^*(P_c^*(\lambda_{c(t+\tau-2)})) \\ &\vdots \\ &= (P_c^*)^\tau \lambda_{ct}. \end{aligned} \tag{7}$$

If the space of possible values for s is divided into a number of discrete cells $k \in \{1, \ldots, K\}$, P_c^* becomes a matrix of transition probabilities:

$$\lambda_{c(t+1)} = P_c^* \cdot \lambda_{ct}, \tag{8}$$

where λ_{ct} is now a $K \times 1$ vector of probabilities that an industry is located in a given grid cell at time t. An element p_c^{kl} of the $K \times K$ matrix P_c^* denotes the probability that an industry beginning in cell k moves to cell l, and may be estimated by counting the number of transitions out of and into each cell. The matrix of transition probabilities yields information on both the degree and pattern of mobility throughout the entire distribution of s. High values of transition probabilities along the diagonal indicate persistence, while larger off-diagonal terms imply greater mobility.[15]

Taking the limit $\tau \to \infty$ in Eq. (7), one obtains the implied ergodic or stationary distribution of s. This is the long-run distribution towards which patterns of specialization are evolving, and corresponds to the eigenvector associated with the largest eigenvalue of the transition probability matrix. It provides information on the evolution of the external shape of the GDP shares distribution.

The degree of mobility in patterns of specialization may be summarized using indices of mobility. These formally evaluate the degree of mobility throughout the entire distribution of GDP shares and facilitate direct cross-country comparisons of

[15] Rather than dividing the space of possible values for shares of GDP into a number of discrete cells, one may continue to treat s as a continuous variable and estimate the stochastic kernel corresponding to P_c^* (see, for example, Quah, 1996b). In the present application, there are too few industries to estimate stochastic kernels for each country. The working paper version of this paper reported stochastic kernels estimated from pooling observations across countries (see Redding, 1999b).

mobility. The first of these indices (M^1, following Shorrocks, 1978; Quah, 1996c) evaluates the trace, tr, of the transition probability matrix. This index thus directly captures the relative magnitude of diagonal and off-diagonal terms, and can be shown to equal the inverse of the harmonic mean of expected durations of remaining in a given grid cell. The second (M^2, following Shorrocks, 1978; Geweke et al., 1986) evaluates the determinant, det, of the transition probability matrix[16]

$$M_c^1 = \frac{K - \mathrm{tr}[P_c^*]}{K-1}, \quad M_c^2 = 1 - |\det(P_c^*)|. \tag{9}$$

Conventional hypothesis testing on the estimated transition probabilities is possible using results from Anderson and Goodman (1957). Under the null hypothesis $p^{kl} = q^{kl}$, the transition probabilities for each state k have an asymptotic χ^2 distribution:

$$\sum_{l=1}^{K} \bar{N}^k \cdot \frac{(p^{kl} - q^{kl})^2}{q^{kl}} \sim \chi^2(K-1), \;\; \bar{N}^k \equiv \sum_{t=0}^{T-1} N^k(t), \tag{10}$$

where p^{kl} are the estimated transition probabilities, q^{kl} are the probabilities of transition under the (known) null, and $N^k(t)$ denotes the number of industries in cell k at time t. This test statistic holds for each state $k = 1, \ldots, K$. Since the transition probabilities are independently distributed across states, we may sum over states, and the resulting test statistic is asymptotically distributed $\chi^2(K(K-1))$.

A key advantage of the statistical techniques used in this paper is that they facilitate an analysis of the evolution of the entire distribution of GDP shares. It becomes possible to explicitly address issues such as persistence versus mobility and changes in the overall degree of specialization. The implementation of the techniques raises a variety of issues of econometric specification, including the length of the transition period, the number of grid cells, and the stability of the operator P_c^* over time. In the empirical analysis below, we present a series of tests that demonstrate the robustness of the results across different econometric specifications.

5. Preliminary data analysis

We consider patterns of specialization across 20 manufacturing industries in seven OECD countries during 1970–90. Industry-level data on current price value-added are taken from the OECD's Structural Analysis Industrial (STAN)

[16]For further discussion of these indices and the circumstances under which they yield transitive rankings of transition probability matrices, see Shorrocks (1978), Geweke et al. (1986), and Quah (1996c).

database, while current price GDP data come from the Penn World Tables 5.6.[17] Endowments of five factors of production are considered: durable goods capital, other capital, arable land, skilled labour, and unskilled labour. The data on both categories of capital goods are from the Penn World Tables 5.6, while the source of information on hectares of arable land is the United Nations Food and Agricultural Organization (FAO).

Skilled and unskilled labour are measured using the proportion of non-production and production workers in total manufacturing employment from the United Nations General Industrial Statistics Database (UNISD). Multiplying these proportions by the economy's total population, we obtain endowments of skilled and unskilled labour. The use of information on non-production/production workers to measure skills follows a large number of authors including Berman et al. (1998) and Feenstra and Hanson (1999).[18] The UNISD data are collected in a consistent way across countries by a single organization. A key advantage over the information on educational attainment in Barro and Lee (1993) is that the data are available annually. The country–industry effect will control for any time-invariant errors of measurement in the factor endowments data. The choice of countries reflects the availability of the UNISD data. Our sample includes Canada, Denmark, Finland, Japan, Sweden, the United Kingdom, and the United States; a group of countries among which one would expect to observe substantial differences in both patterns of specialization and factor endowments.

Table 1 reports the percentage share of total manufacturing value-added in GDP and the share of each industry's value-added in total manufacturing for all seven countries in 1970 and 1990. Manufacturing's share of GDP declines in all countries during the sample period, although the rate of decline varies substantially across countries: from a decline of 30.6% between 1970 and 1990 in the United Kingdom to 10.1% in Denmark. Table 1 also reveals marked changes in the relative importance of individual sectors within manufacturing. Some sectors account for a declining share of manufacturing value-added in all countries (e.g. Textiles and Ferrous metals), while others constitute a rising share of manufacturing value-added in all countries (e.g. Drugs and Radio/TV). Again, the rate of decline or increase varies noticeably across countries: for example, in Radio/TV, the rate of increase varies from 19.8% between 1970 and 1990 in the United Kingdom to 62.5% in Japan and 297.6% in Finland. There are also examples of sectors which account for rising shares of manufacturing value-added in some countries and declining shares in others: for example, the share of the Computing sector displays a rapid increase in all countries except Canada and Sweden where it declines by 37.3% and 52.8%, respectively, between 1970 and 1990.

[17] See Appendix A for further details concerning the data used and an industrial classification.

[18] There is a high time-series correlation between these occupation-based measures of skills and those based on educational attainment: see, for example, Machin and Van Reenen (1998). See Nickell and Bell (1996) for further discussion of educational attainment-based measures of skills.

Table 1
Share of manufacturing in GDP and share of industries in total manufacturing in 1970 and 1990 (%)

Industry	Year	Can	Den	Fin	Jap	Swe	UK	USA
Food	1970	14.86	20.96	13.26	10.57	8.13	13.32	12.33
	1990	14.55	20.54	11.76	10.16	10.18	13.36	10.72
Textiles	1970	8.35	8.89	9.94	7.26	6.17	10.32	7.93
	1990	5.43	4.64	3.87	4.65	2.16	6.24	4.99
Wood	1970	5.78	5.96	9.94	3.55	8.12	2.63	4.34
	1990	6.47	5.60	8.81	2.71	7.66	3.05	4.58
Paper	1970	13.98	11.40	22.46	5.84	14.91	8.45	9.12
	1990	15.81	10.88	20.89	7.39	15.20	11.07	11.56
Chemicals	1970	4.99	4.82	5.08	7.85	4.40	8.07	6.93
	1990	6.31	5.20	5.87	5.60	4.73	8.28	8.62
Drugs	1970	1.02	1.08	0.55	2.08	0.81	1.52	1.37
	1990	1.97	3.68	0.94	2.29	2.12	3.14	2.82
Petroleum	1970	1.34	1.26	2.13	1.22	1.18	1.14	1.47
	1990	1.43	1.19	2.60	0.59	2.50	2.03	2.01
Rubber	1970	2.59	2.76	2.29	3.03	2.71	2.90	2.27
	1990	3.23	3.46	1.83	3.92	2.43	4.42	3.74
Minerals	1970	3.54	7.45	4.22	4.21	3.99	3.51	3.23
	1990	3.19	4.43	4.86	3.61	3.18	3.72	2.41
Ferrous	1970	5.17	1.27	3.19	9.05	7.26	6.31	5.30
	1990	2.98	0.96	3.07	5.84	3.20	3.18	2.67
Non-ferrous	1970	3.80	0.54	1.27	2.26	2.19	1.68	2.06
	1990	3.07	0.32	1.31	1.97	1.45	1.09	1.47
Metals	1970	6.70	7.22	4.51	5.99	9.69	6.57	7.31
	1990	5.54	8.72	6.71	5.90	10.39	5.84	6.73
Office equip.	1970	1.53	0.49	0.13	1.18	1.23	0.79	1.30
	1990	0.96	0.73	1.49	3.26	0.58	2.22	1.87
Non-electrical	1970	6.76	10.70	10.03	9.52	11.63	10.38	10.28
	1990	6.47	14.08	11.30	9.86	13.11	9.48	9.26
Radio, TV	1970	2.63	1.93	0.84	5.57	2.89	3.68	2.67
	1990	3.71	2.41	3.34	9.05	3.52	4.41	5.56
Electrical	1970	3.57	4.78	3.37	5.28	3.97	4.05	4.71
	1990	2.92	3.23	3.65	6.94	3.24	4.28	3.64
Shipbuilding	1970	0.65	3.38	3.38	2.32	1.94	1.78	0.78
	1990	0.52	3.25	2.40	0.60	0.95	1.00	0.67
Motor vehicles	1970	7.27	0.97	1.06	7.83	4.60	5.91	6.52
	1990	9.34	1.18	1.94	8.64	8.19	5.74	4.47
Professional	1970	1.85	1.14	0.44	1.66	0.87	1.87	3.82
	1990	1.66	2.66	1.31	1.82	2.44	1.42	5.06
Other	1970	1.00	1.58	0.94	3.06	0.61	1.08	1.66
	1990	0.89	2.55	0.83	4.67	0.68	1.09	1.96
Total	1970	19.31	17.39	22.43	36.71	22.73	29.46	24.67
	1990	14.71	15.63	19.38	28.51	18.58	20.45	18.87

Notes: see Appendix A for a list of industry names in full and International Standard Industrial Classification (ISIC) Codes. Data sources: OECD STAN database and Penn World Tables 5.6.

Table 2 presents information on the evolution of factor endowments. The econometric specification presented above incorporates a country–industry effect and industry–time dummies. In the fixed effects estimation below, the endowments' coefficients are identified from country-specific variation in factor endowments over time. Table 2 shows that paths of factor accumulation do indeed differ substantially across countries during the sample period. For example, capital accumulation is particularly rapid in Japan. The evolution of numbers of non-production and production workers reflects both changes in skill composition and population growth. Increases in the number of non-production workers are largest in Finland, Japan, and the United States. Numbers of production workers fell in most European countries, but rose in Canada and the United States.[19]

6. Econometric estimation

Having informally examined changes in specialization and factor endowments, this section moves on to econometric estimation. We begin by estimating the structural equation (3) from neoclassical trade theory linking the share of a sector in a country's GDP to underlying economic determinants. The model of distribution dynamics introduced above is then used to analyze the actual evolution of patterns of specialization and their predicted evolution based on changing factor endowments and forces that are common across countries.

6.1. Estimating the neoclassical model

Appendix B presents the results of estimating Eq. (3) for each industry using a panel of data across countries and over time. Estimation is by within groups (fixed effects), and therefore explicitly allows the country–industry effect, η_{cj}, to be correlated with countries' factor endowments. Factor endowments are found to be a statistically significant and quantitatively important determinant of patterns of specialization. Of the 100 coefficients on factor endowments, approximately one-half are statistically significant at the 10% level.

The pattern of estimated coefficients across industries accords with economic priors. In the Paper and Wood industries, where factor endowments might be expected to be particularly important for specialization, we find that four and three of the estimated coefficients on the five endowments are statistically significant at the 10% level. Endowments of non-production workers and durable capital have a negative and statistically significant effect on the Wood industry's share of GDP,

[19] For changes in relative factor endowments to have an important effect on patterns of specialization, we require there to be differences in factor intensity across sectors. The working paper version of this paper (Redding, 1999b) provided evidence of substantial differences in factor intensity at the level of two and three-digit manufacturing industries.

Table 2
Factor endowments

Endowment	Year	Can	Den	Fin	Jap	Swe	UK	US
Non-production	1970	6158	1213	913	43 236	2162	14 414	53 534
	1990	6755	1634	1519	65 880	2626	18 861	77 790
	Δ1990–70	9.70%	34.78%	66.39%	52.37%	21.47%	30.86%	45.31%
Production	1970	15 166	3716	3693	61 109	5881	41 218	151 518
	1990	19 767	3507	3467	57 657	5933	38 550	172 582
	Δ1990–70	30.34%	−5.64%	−6.12%	−5.65%	0.88%	−6.47%	13.90%
Durable capital	1970	28 849	11 959	12 389	170 549	19 169	145 042	580 639
	1990	115 521	26 844	29 560	810 732	65 246	285 313	1 471 855
	Δ1990–70	300.43%	124.46%	138.61%	375.36%	240.38%	96.71%	153.49%
Other capital	1970	171 493	34 038	36 004	454 174	59 071	155 875	1 449 569
	1990	450 760	68 012	87 741	2 043 958	110 147	315 346	2 794 390
	Δ1990–70	162.84%	99.81%	143.70%	350.04%	86.46%	102.31%	92.77%
Arable	1970	43 610	2661	2667	4910	3053	7116	188 735
	1990	45 820	2561	2544	4121	2845	6607	185 742
	Δ1990–70	5.07%	−3.76%	−4.61%	−16.07%	−6.81%	−7.15%	−1.59%

Notes: number of non-production and production workers in thousands; durable and other capital in thousands of 1985 dollars; arable land area in thousands of hectares. Δ1990–70 is the percentage growth in the endowment over the 21-year sample period. Data Sources: Penn World Tables 5.6, United Nations General Industrial Statistics Database (UNISD), and United Nations FAO.

while the effect of endowments of other capital is positive and statistically significant. The two industries where factor endowments are least successful in explaining specialization patterns are Non-metallic Minerals and Shipbuilding. The first most likely reflects the omission of information on endowments of natural resources (some of which will be captured in the fixed effect), while it is plausible that the second is explained by the extensiveness of government intervention in the Shipbuilding industry.

In Fig. 1, we display the estimated industry–year effects. These are normalized so that the 1970 value for each industry is 100, and correspond to the average time-path in the share of that industry in GDP across all seven countries. The figure demonstrates the role of the industry–year effects in generating systematic changes in patterns of specialization. There is a secular rise over time in the share of one group of industries in GDP (e.g. Chemicals and Drugs) and a secular decline in the share of a second group (e.g. Food and Textiles). The implied share of a third group of industries (e.g. Electrical and Rubber) remains broadly constant.

6.2. Specialization dynamics

Estimation of the model of distribution dynamics enables an analysis of intra-distribution dynamics, the evolution of the external shape of the distribution of GDP shares, and their economic determinants. We begin with the evolution of actual shares of sectors in GDP, s_{cjt}. Eq. (8) is estimated by dividing the space of possible values for s into five discrete grid cells and estimating transition probabilities over 5-year periods.[20] The boundaries between grid cells are chosen such that industry–year observations are divided roughly equally between the cells, and each cell corresponds to approximately one quintile of the distribution of GDP shares across industries and time.

Table 3 presents estimation results for the United States. Panel (A) of the table is concerned with the evolution of actual shares of sectors in GDP, and its interpretation is as follows. The numbers in parentheses in the first column are the total number of industry–year observations in a particular grid cell over the sample period, while the first row of numbers denotes the upper endpoint of the corresponding grid cell. Thereafter, each row reports the estimated probability of passing from one state into another. For example, the second row of numbers presents (reading across from the second to the sixth column) the probability of remaining in the lowest state and then the probability of moving into the lower-intermediate, intermediate, higher-intermediate, and highest state successively. The final two rows of the upper panel of the table give the initial

[20] All estimation is undertaken using Danny Quah's TSRF econometrics package, which can be downloaded from http://econ.lse.ac.uk/staff/dquah/tsrf.html. Responsibility for any results, opinions and errors is the author's alone.

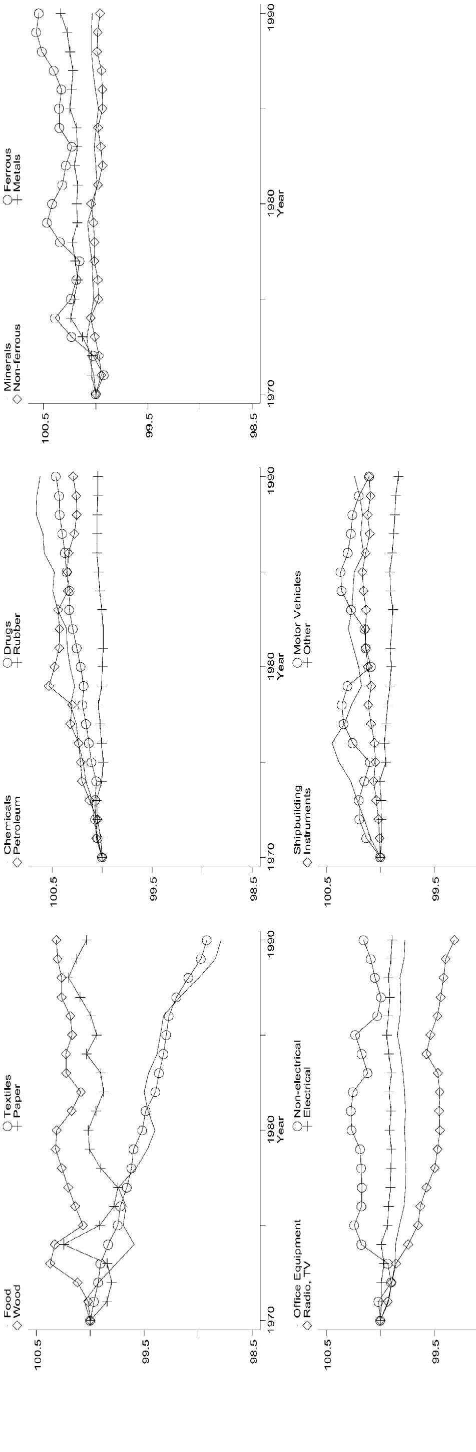

Fig. 1. Industry–year effects, fixed effects estimation, 1970 = 100.

Table 3
Transition probabilities, United States, shares of GDP, 5-year transitions, 1971:76–1985:90

	Upper endpoint (% GDP)				
(*A*) *Actual*, s_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(61)	0.79	0.21	0.00	0.00	0.00
(59)	0.22	0.61	0.17	0.00	0.00
(53)	0.02	0.17	0.74	0.08	0.00
(63)	0.00	0.06	0.25	0.67	0.02
(64)	0.00	0.00	0.00	0.20	0.80
Initial	0.250	0.150	0.100	0.200	0.300
Ergodic	0.351	0.317	0.264	0.063	0.005
(*B*) *Normalized*, $s_{cjt} / \bar{s}_{ct}$					
Number	(0.407)	(0.676)	(1.047)	(1.567)	(>1.567)
(61)	0.70	0.28	0.02	0.00	0.00
(59)	0.19	0.64	0.17	0.00	0.00
(61)	0.02	0.10	0.74	0.15	0.00
(58)	0.00	0.05	0.10	0.74	0.10
(61)	0.00	0.00	0.00	0.16	0.84
Initial	0.250	0.150	0.200	0.200	0.200
Ergodic	0.154	0.222	0.245	0.233	0.147
(*C*) *Fitted*, s^{P}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(60)	0.80	0.20	0.00	0.00	0.00
(56)	0.21	0.68	0.11	0.00	0.00
(58)	0.00	0.19	0.78	0.03	0.00
(65)	0.00	0.00	0.26	0.71	0.03
(61)	0.00	0.00	0.00	0.20	0.80
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.394	0.367	0.208	0.027	0.004
(*D*) *Endowment*, s^{E}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(50)	0.98	0.02	0.00	0.00	0.00
(71)	0.14	0.86	0.00	0.00	0.00
(55)	0.00	0.25	0.65	0.09	0.00
(64)	0.00	0.00	0.31	0.69	0.00
(60)	0.00	0.00	0.00	0.00	1.00
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.000	0.000	0.000	0.000	1.000
(*E*) *Ind–year*, s^{I}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(62)	0.90	0.10	0.00	0.00	0.00
(53)	0.08	0.68	0.25	0.00	0.00
(41)	0.00	0.17	0.71	0.12	0.00
(59)	0.00	0.00	0.20	0.61	0.19
(85)	0.00	0.00	0.00	0.11	0.89
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.139	0.179	0.257	0.154	0.271

Notes: $\bar{s}_{ct} \equiv (1/n)\Sigma_j s_{cjt}$. Initial is the distribution of industries across grid cells in 1970. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

distribution of industries across grid cells in 1970 and the ergodic distribution implied by the estimated transition probability matrix.

We find evidence of substantial mobility in patterns of specialization. In the United States, the estimated probability of moving out of a quintile of the distribution after 5 years ranges from 0.39 to 0.20. Mobility is smallest at the extremes of the distribution of GDP shares—in the lower and upper quintiles—and greatest in the centre. A comparison of the initial and ergodic distributions provides evidence of the general decline in the size of manufacturing industries during the sample period. The ergodic distribution reveals evidence of a polarization of GDP shares towards the bottom three quintiles of the distribution.

The estimated transition probabilities in Panel (A) of Table 3 capture two effects. First, the general decline in the size of manufacturing will tend to induce the average industry to move from a higher to a lower grid cell. Second, individual manufacturing industries will move between grid cells because they experience *different* rates of growth and decline, resulting in changes in their *relative* position within the distribution of GDP shares. The theoretical model of Section 3 implies that both phenomena are of interest and should be included in the empirical analysis. Manufacturing's decline is one of the features about the evolution of patterns of specialization that the model seeks to explain. For example, the contribution of changes in world relative prices (associated with the development of manufacturing centres in East Asia and elsewhere) and of pervasive technological change will be captured in the estimated industry–year dummies. Moreover, a number of manufacturing industries experience increases in their share of a country's GDP during the sample period. This is reflected in the upward trend over time in the industry–year effects for a number of sectors in Fig. 1.

Nonetheless, in order to demonstrate that the finding of mobility is not driven by the decline in the average size of manufacturing sectors and that changes in the relative size of individual industries are important, we undertake the following robustness test. At each point in time, the share of a manufacturing industry in a country's GDP, s_{cjt}, is normalized by the average share of all manufacturing industries, $\bar{s}_{ct} = (1/n)\Sigma_j\, s_{cjt}$. Transition probabilities are then re-estimated using the normalized variable, $\tilde{s}_{cjt} \equiv s_{cjt}/\bar{s}_{ct}$. The normalization removes any country-specific decline in the average GDP share of manufacturing industries, and means that the analysis now captures specialization *within manufacturing*. The cross-section mean of $\tilde{s}_{cjt}$ is 1 at each period in time, and a value greater than 1 denotes an industry with an above average share of a country's GDP.

Panel (B) of Table 3 reports estimation results for the United States, where the mean value of s_{cjt} across industries in 1970 was 1.177. Boundaries between grid cells are again chosen such that industry–year observations are distributed roughly equally across cells, and we are therefore again concerned with movements between quintiles of the distribution. The estimated transition probabilities now only capture changes in the *relative* position of industries within the distribution of GDP shares. Again, we find evidence of mobility in patterns of specialization. The estimated probability of moving out of one quintile of the distribution in the United States varies from 0.36 to 0.16. We find no evidence of increased specialization within the manufacturing sector. The greater mass of the ergodic distribution is concentrated in the middle three quintiles, and there is actually a decrease in mass in the upper and lower quintiles relative to the initial distribution in 1970.

6.3. Economic determinants of specialization dynamics

Having shown that changes in the *relative* size of individual manufacturing industries are driving the empirical findings of mobility, we now consider the economic determinants for observed changes in patterns of specialization. We return to the use of un-normalized GDP shares as implied by theory. Panels (C)–(E) of Table 3 present results for fitted values of shares of GDP (s^{P}_{cjt}, from Eq. (4)), predicted values holding industry–year effects constant at their beginning of sample values (the endowment predictions, s^{E}_{cjt}), and predicted values holding factor endowments constant at their beginning of sample values (the industry–year predictions, s^{I}_{cjt}). In each case, exactly the same boundaries between grid cells are used as for actual GDP shares. The estimated transition probabilities therefore tell us to what extent the model or the relevant component of the model can explain observed movements of industries between quintiles of the distribution of actual GDP shares. By construction, the three sets of predicted values are equal at the beginning of the sample period, and the initial distribution of industries across grid cells is therefore the same in panels (C)–(E).

Comparing Panel (C) with the results for actual shares of GDP in Panel (A), the estimated values of transition probabilities generally lie close together, implying that the model is reasonably successful at explaining observed mobility in patterns of specialization. Over 5 years with the fitted values, the estimated probability of moving out of one quintile of the distribution of GDP shares ranges from 0.32 to 0.20. Estimated values for the diagonal elements of the transition probability matrix are higher in the middle three quintiles of the distribution when using fitted, s^{P}_{cjt}, rather than actual, s_{cjt}, values. This suggests a potential role for other considerations in explaining mobility in the centre of the distribution, including country-specific changes in technology or relative prices that are uncorrelated with factor endowments. This is consistent with the theoretical model presented earlier.

The predicted movements of industries within the distribution of GDP shares using the fitted values are the result of a combination of both changes in endowments and industry–year effects. The lower two panels of Table 3 present estimation results using endowment predictions, s^{E}_{cjt}, and industry–year predictions, s^{I}_{cjt}. In principle, these may individually display either more or less mobility than when using the fitted values. If the changes in a country's pattern of specialization induced by factor endowments tend to reinforce those brought about by industry–year effects, predicted movements of industries within the GDP shares distribution will be smaller when considering one of these sets of influences than when considering both together. In contrast, if the changes in specialization induced by factor endowments tend to offset those brought about by industry–year effects, examining factor endowments (or industry–year effects) individually will predict larger movements of industries within the GDP shares distribution.

In the case of the United States, less mobility in patterns of specialization is observed with the endowment or industry–year predictions individually than with fitted or actual values of GDP shares. The estimated values of transition probabilities along the diagonal are generally larger in the bottom two panels of the table. This is particularly true for the endowment predictions which display the least mobility. Therefore, over a 5-year time horizon, considerations that are common across countries are quantitatively more important in explaining changes in US patterns of specialization than country-specific changes in factor endowments.

The *pattern* of mobility with the endowment predictions is also of interest. These are characterized by extreme immobility in the lower and upper quintiles of the GDP shares distribution, combined with a level of mobility in the centre of the distribution not dissimilar (and in fact higher in the third quintile) than found with the industry–year predictions, fitted values, and actual shares of GDP. During the sample period, factor endowments were responsible for a polarization in patterns of specialization in the United States, reinforcing specialization in sectors which initially had high shares of GDP, preserving low shares of GDP in sectors that were initially small, and reducing the number of sectors with intermediate values for shares of GDP.

In Table 4, we examine how these results are affected by allowing transitions to occur over a longer time horizon of 10 years. Exactly the same boundaries between grid cells as before are used. Over longer time horizons, more mobility in patterns of specialization is observed. In the United States, the estimated probability of moving out of a quintile of the distribution after 10 years ranges from 0.83 to 0.38. Mobility remains greatest in the centre of the distribution and smallest at the extremes. The relative contribution of factor endowments to changes in patterns of specialization is now greater: the average value of the diagonal elements of the estimated transition probability matrix with the endowments predictions is lower than with the industry–year predictions. A similar pattern of mobility is also observed. The endowment predictions exhibit extreme immobility in the lower and upper quintiles of the GDP shares distribution, combined with much greater mobility in the centre of the distribution.

These results are consistent with the idea that changes in relative factor abundance occur gradually and take time to manifest themselves in substantial changes in patterns of specialization. They also confirm the role of US factor endowments in reinforcing specialization in sectors which began with high shares of GDP and acting against specialization in sectors which began with low shares of GDP.

Table 4
Transition probabilities, United States, shares of GDP, 10-year transitions, 1971:81–1980:90

	Upper endpoint (% GDP)				
Actual, s_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(42)	0.62	0.38	0.00	0.00	0.00
(35)	0.46	0.17	0.29	0.09	0.00
(32)	0.03	0.38	0.59	0.00	0.00
(42)	0.00	0.19	0.43	0.36	0.02
(49)	0.00	0.00	0.00	0.41	0.59
Initial	0.250	0.150	0.100	0.200	0.300
Ergodic	0.389	0.306	0.260	0.042	0.002
Fitted, s^{P}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(40)	0.55	0.45	0.00	0.00	0.00
(36)	0.47	0.33	0.19	0.00	0.00
(33)	0.03	0.30	0.67	0.00	0.00
(45)	0.00	0.02	0.51	0.47	0.00
(46)	0.00	0.00	0.00	0.35	0.65
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.407	0.374	0.218	0.000	0.000
Endowment, s^{E}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(31)	0.97	0.03	0.00	0.00	0.00
(44)	0.23	0.77	0.00	0.00	0.00
(38)	0.11	0.37	0.34	0.18	0.00
(47)	0.00	0.06	0.51	0.43	0.00
(40)	0.00	0.00	0.00	0.00	1.00
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.000	0.000	0.000	0.000	1.000
Ind-year, s^{I}_{cjt}					
Number	(0.410)	(0.690)	(1.050)	(1.660)	(>1.660)
(42)	0.86	0.10	0.05	0.00	0.00
(35)	0.11	0.66	0.23	0.00	0.00
(27)	0.00	0.15	0.81	0.04	0.00
(39)	0.00	0.00	0.15	0.64	0.21
(57)	0.00	0.00	0.00	0.12	0.88
Initial	0.200	0.150	0.150	0.300	0.200
Ergodic	0.168	0.210	0.378	0.091	0.152

Notes: initial is the distribution of industries across grid cells in 1970. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

6.4. Indices of mobility

Table 5 uses formal indices of mobility to evaluate the overall degree of mobility in patterns of specialization. Results are reported for the United States and the other six countries in the sample.[21] When estimating transition probabilities for the other countries, boundaries between grid cells are again chosen such that industry–year observations are allocated roughly equally across the cells. We are therefore always concerned with movements of industries between quintiles of the GDP shares distribution. For a given country, the same grid boundaries are used for actual shares of GDP, fitted shares of GDP, endowment predictions, and industry–year predictions. The estimated transition probabilities again capture the ability of the model or the relevant component of the model to explain observed movements of industries between quintiles of the distribution of actual GDP shares. Mobility indices are evaluated based on the results for actual shares of GDP, fitted shares of GDP, endowment predictions, and industry–year predictions.

Table 5 also reports the ratio of the mobility indices for the endowment and industry–year predictions. This provides a measure of the relative importance of these two sets of considerations in explaining changes in patterns of specialization. Levels of mobility vary across the seven countries. With 5-year transitions, Japan and Sweden exhibit the highest levels; Canada, the United Kingdom, and United States have intermediate levels; Denmark and Finland display the least. A similar pattern is observed with 10-year transitions. Mobility remains high in Japan and is low in Denmark and Finland. Over the longer time horizon, the United Kingdom and United States display higher levels of mobility relative to the other countries in the sample.

We saw above that the model was reasonably successful at explaining changes in US patterns of specialization. This is confirmed for the other countries in Table 5, where levels of mobility using the fitted values for shares of GDP are typically close to those using the actual values. The conclusions concerning the relative importance of factor endowments and industry–year effects in the United States are also confirmed using the formal indices of mobility. A similar pattern of results is found for the other six countries. Over 5-year periods, common cross-country effects are more important in explaining observed changes in patterns of specialization than factor endowments for the majority of countries. Over 10-year periods, factor endowments become relatively more important in each country in the sample. Over the longer time horizon, factor endowments account for most of the observed mobility in specialization patterns in all countries except Canada and Sweden.

The two countries where the relative contribution of factor endowments to

[21] In the interests of brevity, full estimation results for the other countries are not reported. These are contained in an appendix available from the author on request.

Table 5
Mobility indices by country

Country	Variable	5-year		10-year	
		M_c^1	M_c^2	M_c^1	M_c^2
Canada	Actual, s_{cjt}	0.345	0.856	0.463	0.950
	Fitted, s_{cjt}^{P}	0.360	0.873	0.510	0.990
	Endowment, s_{cjt}^{E}	0.253	0.719	0.463	0.941
	Ind–year, s_{cjt}^{I}	0.338	0.874	0.465	1.000
	E/I ratio	75%	82%	100%	94%
Denmark	Actual, s_{cjt}	0.273	0.748	0.388	0.891
	Fitted, s_{cjt}^{P}	0.285	0.768	0.418	0.898
	Endowment, s_{cjt}^{E}	0.213	0.645	0.365	0.900
	Ind–year, s_{cjt}^{I}	0.285	0.824	0.318	0.862
	E/I ratio	75%	78%	115%	104%
Finland	Actual, s_{cjt}	0.288	0.764	0.343	0.821
	Fitted, s_{cjt}^{P}	0.288	0.780	0.453	0.948
	Endowment, s_{cjt}^{E}	0.348	0.866	0.515	0.980
	Ind–year, s_{cjt}^{I}	0.200	0.603	0.333	0.819
	E/I ratio	174%	144%	155%	120%
Japan	Actual, s_{cjt}	0.420	0.934	0.618	1.003
	Fitted, s_{cjt}^{P}	0.245	0.684	0.515	0.967
	Endowment, s_{cjt}^{E}	0.303	0.780	0.515	0.962
	Ind–year, s_{cjt}^{I}	0.213	0.639	0.293	0.784
	E/I ratio	142%	122%	176%	123%
Sweden	Actual, s_{cjt}	0.440	0.939	0.498	0.965
	Fitted, s_{cjt}^{P}	0.310	0.802	0.513	0.971
	Endowment, s_{cjt}^{E}	0.200	0.600	0.325	0.809
	Ind–year, s_{cjt}^{I}	0.303	0.788	0.393	0.888
	E/I ratio	66%	76%	83%	91%
United Kingdom	Actual, s_{cjt}	0.345	0.841	0.563	1.004
	Fitted, s_{cjt}^{P}	0.263	0.745	0.440	0.945
	Endowment, s_{cjt}^{E}	0.175	0.550	0.290	0.769
	Ind–year, s_{cjt}^{I}	0.233	0.685	0.245	0.704
	E/I ratio	75%	80%	118%	109%
United States	Actual, s_{cjt}	0.348	0.847	0.668	1.020
	Fitted, s_{cjt}^{P}	0.308	0.792	0.583	1.015
	Endowment, s_{cjt}^{E}	0.205	0.647	0.373	0.960
	Ind–year, s_{cjt}^{I}	0.303	0.809	0.288	0.776
	E/I ratio	68%	80%	130%	124%

Notes: $M_c^1 = (K - \mathrm{tr}[P_c^*])/(K-1)$, $M_c^2 = 1 - |\det(P_c^*)|$; see main text for further discussion of the mobility indices. E/I ratio is the ratio of the mobility indices for the endowment and industry–year predictions expressed as a percentage.

changes in specialization is greatest are Japan and Finland. Even over 5-year periods, factor endowments explain most of the observed mobility in these countries' patterns of specialization. These findings are consistent with the preliminary data analysis in Table 2. Japan displays the highest rates of accumulation of durable capital and other capital, and exhibits the second highest rate of accumulation of non-production workers. Similarly, Finland has the highest rate of increase of non-production workers and the second highest rate of decrease in production workers.

6.5. Statistical significance

Table 6 examines the statistical significance of the differences between the transition probability matrices estimated using actual shares of GDP, fitted shares of GDP, endowment predictions, and industry–year predictions. In each case, the null hypothesis is that the Data Generation Process (DGP) equals the matrix of transition probabilities estimated using actual GDP shares. We test whether the matrices estimated using the fitted values, endowment predictions, and industry–year predictions are statistically significantly different from this null. In the

Table 6
Statistical significance, 5-year transitions

Country	Fitted, s^{P}_{cjt} (p-value)	Endowment, s^{E}_{cjt} (p-value)	Ind–year, s^{I}_{cjt} (p-value)
Canada	0.923 *(Accept)*	0.010 *(Reject)*	0.000 *(Reject)*
Denmark	0.471 *(Accept)*	0.174 *(Accept)*	0.008 *(Reject)*
Finland	0.044 *(Reject)*	0.001 *(Reject)*	0.510 *(Accept)*
Japan	0.000 *(Reject)*	0.006 *(Reject)*	0.000 *(Reject)*
Sweden	0.491 *(Accept)*	0.000 *(Reject)*	0.000 *(Reject)*
United Kingdom	0.785 *(Accept)*	0.023 *(Reject)*	0.000 *(Reject)*
United States	0.999 *(Accept)*	0.000 *(Reject)*	0.000 *(Reject)*

Notes: null hypothesis is that the Data Generation Process (DGP) equals the matrix of transition probabilities estimated using actual GDP shares. We test whether the matrices estimated using the fitted values, endowment predictions, and industry–year predictions are statistically significantly different from this null. Test statistic is distributed $\chi^2(20)$; reported rejections are at the 5% level.

interests of brevity, the analysis is restricted to the transition probability matrices estimated over 5-year periods.

Column (2) reports the results using fitted shares of GDP, where we are unable to reject the null hypothesis at the 5% level for a majority of countries. This provides further evidence of the model's ability to explain observed mobility in patterns of specialization. The exceptions are Finland and Japan, although only the Japanese matrix is statistically significantly different from the null at the 1% level. Thus, while factor endowments are important in accounting for changes in specialization in Japan, there remains a potential role for country-specific changes in technology and relative prices. Columns (3) and (4) present the results using endowment and industry–year predictions respectively. The null hypothesis is rejected at the 5% level in all countries, except for the endowments predictions in Denmark and the industry–year predictions in Finland. In almost all cases, the distinctive predictions of factor endowments for patterns of specialization noted above are statistically significantly different from the null that the DGP is given by actual specialization dynamics.

6.6. External shape

Table 7 examines the evolution of the external shape of the distribution of GDP shares in the other countries. For each country, we report the initial distribution of industries across grid cells and the ergodic distribution implied by the transition probability matrix estimated using actual shares of GDP and with 5-year transitions.

In Canada, Japan, Sweden, and the United Kingdom, the decline in the size of manufacturing is reflected in the polarization of the ergodic distribution towards the bottom two quintiles. In Finland and Denmark, the ergodic distribution shows an increase in the number of industries located at intermediate values for shares of GDP relative to the initial distribution, providing evidence of a decrease in the overall degree of specialization in these countries. If actual shares of GDP are normalized by their mean across industries, we find no evidence of an increase in specialization within manufacturing for any of the countries in the dataset. In Finland and Denmark, there is again an increase in the number of industries located at intermediate values.

6.7. Robustness of results

Finally, we undertake a series of econometric robustness tests.[22] Our results are robust to each of these tests. First, the space of values for shares of GDP was divided into four grid cells rather than five and transition probability matrices were

[22] Further details of the robustness tests are contained in an appendix available from the author on request.

Table 7
Evolution of the external shape of the distribution of actual shares of GDP, s_{cjt}, 5-year transitions

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5
Canada					
Initial	0.150	0.200	0.200	0.150	0.300
Ergodic	0.302	0.388	0.215	0.077	0.017
Denmark					
Initial	0.250	0.200	0.100	0.150	0.300
Ergodic	0.125	0.112	0.440	0.216	0.108
Finland					
Initial	0.300	0.100	0.200	0.150	0.250
Ergodic	0.179	0.295	0.308	0.183	0.037
Japan					
Initial	0.150	0.250	0.100	0.200	0.300
Ergodic	0.431	0.322	0.138	0.076	0.033
Sweden					
Initial	0.250	0.100	0.200	0.200	0.250
Ergodic	0.314	0.415	0.151	0.063	0.056
United Kingdom					
Initial	0.150	0.250	0.150	0.200	0.250
Ergodic	0.596	0.294	0.077	0.027	0.006
United States					
Initial	0.250	0.150	0.100	0.200	0.300
Ergodic	0.351	0.317	0.264	0.063	0.005

Notes: initial is the distribution of industries across grid cells in 1970 and ergodic is the stationary distribution implied by the transition probability matrices estimated for actual shares of GDP, s_{cjt}.

re-estimated over 5-year and 10-year time periods. We again find evidence of substantial mobility in patterns of specialization. Transition probabilities estimated using the fitted values for shares of GDP are close to those estimated using the actual values. The relative importance of factor endowments in explaining changes in patterns of specialization is greater over longer time horizons, and there is no evidence of an increase in countries' overall degree of specialization over time.

Second, we return to the case of five grid cells and examine the robustness of the results to estimating transition probabilities over 3-year and 8-year time periods rather than over periods of 5 and 10 years. Again, a very similar pattern of results is observed with factor endowments becoming more important as explanations for mobility over longer time horizons. Third, we examine the stability of the estimated transition probability matrices over time. Transition probabilities are re-estimated excluding the last 5 years of the sample period and compared with those estimated for the full sample (this ensures a minimum of over 30 observations in each grid cell). We test the null hypothesis that the transition probabilities estimated for the full sample are the result of a Data Generation

Process (DGP) given by the matrix estimated excluding the last 5 years. For each of the countries in the sample, we are unable to reject the null hypothesis at conventional levels of statistical significance.

Fourth, we examine the sensitivity of the results to the inclusion of individual industries. Each industry was sequentially excluded from the sample and transition probability matrices were re-estimated. There is little variation in the estimated transition probabilities across the 20 sets of estimation results. The sample mean of each element of the transition probability matrix lies close to the value estimated for the full sample above. The sample standard deviation of each element of the matrix across the 20 sets of estimation results is an order of magnitude smaller than the estimated transition probabilities.

7. Conclusions

Much of the existing empirical trade literature is concerned with the static predictions of international trade theory for cross-section patterns of specialization at a point in time. This contrasts with the theoretical literature on trade and growth, which emphasizes that comparative advantage is dynamic and evolves endogenously over time. This paper proposes an empirical framework for analyzing the dynamics of specialization; the framework is implemented using disaggregated data on 20 manufacturing industries in seven OECD countries during 1970–90.

The analysis begins with a measure of a country's extent of specialization in an industry derived directly from neoclassical trade theory: the share of the industry in that country's GDP. A country's pattern of specialization at a point in time is characterized by the distribution of this measure across industries, while the dynamics of specialization correspond to the evolution of this entire distribution over time. We employ a model of distribution dynamics from the cross-country growth literature that is explicitly suited to an analysis of the evolution of entire distributions. Transition probability matrices are estimated for each of the seven countries in our sample: Canada, Denmark, Finland, Japan, Sweden, United Kingdom, and United States. There is evidence of substantial mobility in patterns of specialization, with Japan typically displaying the highest levels of mobility, and Denmark and Finland displaying the least.

Over 5-year time periods, considerations which are common across countries, including changes in prices on world markets and common changes in technical efficiency, explain most of the observed mobility in patterns of specialization for the majority of countries. A notable exception is Japan. Even over 5-year time periods, the substantial changes in Japan's pattern of specialization are largely explained by the rapid accumulation of physical and human capital. Over longer time horizons of 10 years, common cross-country effects remain substantial but country-specific changes in factor endowments become relatively more important. In the literature on international trade and wage inequality, there is considerable debate concerning the speed at which ‘‘the Heckscher–Ohlin clock ticks.’’ This finding suggests that it takes a number of years for gradual changes in relative factor abundance to manifest themselves in substantial changes in patterns of specialization.

We find no evidence of an increase in the extent to which countries’ production is concentrated in a few industries. Indeed, in Finland and Denmark, there is an increase in the number of industries located at intermediate values for shares of GDP, suggesting a decrease in specialization in these countries. The results were shown to be robust to the number of grid cells chosen, the exact length of the transition periods considered, and to the exclusion of individual industries. We find no evidence of a statistically significant change in the estimated transition probability matrices over time.

Taken together, our results show how statistical models of distribution dynamics may be used to shed light on a variety of issues relating to specialization dynamics, bringing empirical work closer to the focus on dynamic comparative advantage evident in theoretical research on trade and growth.

Acknowledgements

This paper was produced as part of the Globalisation Programme of the ESRC funded Centre for Economic Performance, London School of Economics, and is a revised version of CEPR Discussion Paper 2287. I am especially grateful to James Harrigan, two anonymous referees, and Jonathan Temple for extremely helpful comments and suggestions. I am also grateful to Richard Baldwin, Simon Evenett, Rachel Griffith, Gordon Hanson, Wolfgang Keller, Peter Neary, Stephen Nickell, Victor Norman, Henry Overman, James Proudman, Danny Quah, Tony Venables, Alan Winters, participants in seminars at the London School of Economics, the CEPR European Research Workshop in International Trade (ERWIT), the Purdue conference on Empirical Investigations in International Trade (EIIT), the Tilburg Conference on Dynamics, Economic Growth, and International trade (DEGIT), and the World Bank for helpful comments. I would like to thank Sandra Bulli, Paco Requena-Silvente, Martin Stewart, and Mercedes Vera-Martin for research assistance. I am grateful to John Van Reenen for supplying the production/non-production workers data. Any opinions, results, and errors are the responsibility of the author alone.

Appendix A. Data appendix

OECD Structural Analysis Industrial (STAN) database: data on current price value-added (US dollars) for 20 manufacturing industries (International Standard

Industrial Classification (ISIC)), 1970–90. *Penn World Tables 5.6:* data on current price GDP per capita (US dollars), population (thousands), non-residential capital stock (1985 US dollars), and Producer durables (% of non-residential capital stock, 1985 US dollars), 1970–90. *United Nations General Industrial Statistics Database (UNISD):* data on the proportion of non-production and production workers in total manufacturing, 1970–90. See Berman et al. (1998) and Machin and Van Reenen (1998) for further discussion of the data. *FAO Arable Land Data:* data on hectares of arable land (thousands) from the United Nations Food and Agricultural Organization (FAOSTAT), 1970–90. *Country Coverage:* Canada, Denmark, Finland, Japan, Sweden, United Kingdom, and United States. *Industrial Composition (ISIC Code):* 1, Food, Drink and Tobacco (3100); 2, Textiles, Footwear and Leather (3200); 3, Wood, Cork and Furniture (3300); 4, Paper, Print and Publishing (3400); 5, Chemicals excl. Drugs (3512); 6, Drugs and Medicines (3522); 7, Petroleum Refineries and Products (3534); 8, Rubber and Plastic Products (3556); 9, Non-metallic Minerals (3600); 10, Ferrous Metals (3710); 11, Non-ferrous Metals (3720); 12, Metal Products (3810); 13, Office and Computing Equipment (3825); 14, Non-electrical Machinery (3829); 15, Radio, TV and Communication (3832); 16, Other Electrical Machinery (3839); 17, Shipbuilding and Repairing (3841); 18, Motor Vehicles (3843); 19, Professional Goods (3850); 20, Other Manufacturing (3900).

Appendix B. Estimating the neoclassical model

Industry		Industry		Industry	
1. Food		*5. Chemicals*		*9. Minerals*	
nprod	−0.244	nprod	−0.371	nprod	−0.130
	(0.310)		(0.537)		(0.143)
prod	2.008	prod	1.599	prod	0.024
	(0.653)		(0.921)		(0.222)
dkap	−0.264	dkap	−0.655	dkap	−0.103
	(0.173)		(0.236)		(0.088)
okap	−0.743	okap	−0.677	okap	−0.005
	(0.210)		(0.279)		(0.104)
arable	−0.257	arable	−0.570	arable	0.001
	(1.057)		(1.337)		(0.371)
R^2	0.927	R^2	0.926	R^2	0.927

Industry		Industry		Industry	
2. Textiles		*6. Drugs*		*10. Ferrous*	
nprod	−0.265	nprod	−1.596	nprod	−0.039
	(0.084)		(0.420)		(0.196)
prod	−0.664	prod	−0.020	prod	1.538
	(0.190)		(0.814)		(0.349)
dkap	0.043	dkap	−0.057	dkap	−0.303
	(0.055)		(0.273)		(0.115)
okap	−0.279	okap	−0.100	okap	−0.181
	(0.067)		(0.255)		(0.138)
arable	0.458	arable	−1.421	arable	−1.838
	(0.313)		(1.366)		(0.623)
R^2	0.962	R^2	0.891	R^2	0.935
3. Wood		*7. Petroleum*		*11. Non-Ferrous*	
nprod	−0.692	nprod	−0.281	nprod	0.123
	(0.161)		(0.405)		(0.153)
prod	−0.341	prod	1.677	prod	0.131
	(0.303)		(0.748)		(0.252)
dkap	−0.199	dkap	−0.183	dkap	−0.230
	(0.121)		(0.245)		(0.093)
okap	0.320	okap	−0.689	okap	0.587
	(0.148)		(0.245)		(0.109)
arable	−0.462	arable	−3.653	arable	−0.511
	(0.439)		(1.241)		(0.305)
R^2	0.964	R^2	0.806	R^2	0.922
4. Paper		*8. Rubber*		*12. Metals*	
nprod	−0.666	nprod	−1.625	nprod	−0.148
	(0.383)		(0.497)		(0.076)
prod	−1.823	prod	−0.411	prod	−0.092
	(0.789)		(0.847)		(0.208)
dkap	1.223	dkap	0.456	dkap	0.121
	(0.244)		(0.325)		(0.053)
okap	−0.763	okap	−0.519	okap	0.061
	(0.278)		(0.368)		(0.077)
arable	−1.833	arable	−3.873	arable	−0.805
	(1.139)		(1.617)		(0.270)
R^2	0.940	R^2	0.948	R^2	0.987

Industry		Industry	
13. Office Equip.		*17. Shipbuilding*	
nprod	0.203	nprod	0.064
	(0.400)		(0.111)
prod	3.506	prod	0.098
	(0.849)		(0.253)
dkap	−0.998	dkap	−0.072
	(0.310)		(0.077)
okap	0.336	okap	0.015
	(0.269)		(0.097)
arable	−4.441	arable	0.258
	(1.529)		(0.398)
R^2	0.965	R^2	0.961
14. Non-electrical		*18. Motor Vehicles*	
nprod	−0.585	nprod	0.883
	(0.199)		(0.223)
prod	−0.142	prod	2.346
	(0.492)		(0.610)
dkap	0.387	dkap	−0.181
	(0.141)		(0.182)
okap	−0.689	okap	−0.681
	(0.115)		(0.172)
arable	−1.333	arable	0.657
	(0.928)		(0.917)
R^2	0.683	R^2	0.895
15. Radio, TV		*19. Professional*	
nprod	0.174	nprod	−0.194
	(0.140)		(0.322)
prod	0.385	prod	1.417
	(0.281)		(0.619)
dkap	0.276	dkap	0.675
	(0.081)		(0.204)
okap	−0.620	okap	−0.993
	(0.083)		(0.196)
arable	−1.870	arable	−1.307
	(0.494)		(0.946)
R^2	0.942	R^2	0.943

Industry		Industry	
16. Electrical		*20. Other*	
nprod	1.022	nprod	−0.609
	(0.293)		(0.300)
prod	0.919	prod	−0.016
	(0.576)		(0.641)
dkap	−0.185	dkap	−0.302
	(0.206)		(0.213)
okap	0.860	okap	−0.031
	(0.246)		(0.195)
arable	0.209	arable	1.594
	(0.913)		(1.105)
R^2	0.940	R^2	0.924

Notes: dependent variable is the percentage share of sector in GDP. Independent variables are as follows: nprod is log number of non-production workers (thousands); prod is log number of production workers (thousands); dkap is log stock of durable capital (thousands of 1985 US dollars); okap is log stock of other capital (thousands of 1985 US dollars); arable is log arable land (thousands of hectares). See Appendix A for a list of industry names in full and International Standard Industrial Classification (ISIC) codes. Sample size is 147 observations per industry; time-period is 1970–90. Standard errors are Huber–White heteroscedasticity robust. All industry regressions include a full set of year dummies and country fixed effects.

References

Acemoglu, D., 1998. Why do new technologies complement skills? Directed technical change and wage inequality. Quarterly Journal of Economics 113 (4), 1055–1089.

Amiti, M., 1999. Specialisation patterns in Europe. Weltwirtschaftliches Archiv 134 (4), 573–593.

Anderson, T., Goodman, L., 1957. Statistical inference about Markov chains. Annual of Mathematical Statistics 28, 89–110.

Balassa, B., 1979. The changing pattern of comparative advantage in manufactured goods. Review of Economics and Statistics 61 (2), 259–266.

Barro, R., Lee, J., 1993. International comparisons of educational attainment. Journal of Monetary Economics 32 (3), 363–394.

Berman, E., Bound, J., Machin, S., 1998. Implications of skill-biased technological change: international evidence. Quarterly Journal of Economics November, 1245–1279.

Bernstein, J., Weinstein, D., 1998. Do endowments predict the location of production? Evidence from national and international data. NBER Working Paper 6815.

Bowen, H., 1983. Changes in the international distribution of resources and their impact on US comparative advantage. Review of Economics and Statistics 65, 402–414.

Bowen, H., Leamer, E., Sveikauskas, L., 1987. Multicountry, multifactor tests of the factor abundance theory. American Economic Review 77, 791–809.

Brasili, A., Epifani, P., Helg, R., 1999. On the dynamics of trade patterns. Paper presented at Tilburg Conference on Dynamics, Growth and International Trade. University of Bocconi, mimeo.

Caves, D., Christensen, L., Diewert, E., 1982. The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica 50, 1393–1414.

Davis, D., Reeve, T., 1997. Human capital, unemployment, and relative wages in a global economy. NBER Working Paper 6133.

Davis, D., Weinstein, D., Bradford, S., Shimpo, K., 1997. Using international and Japanese regional data to determine when the factor abundance theory of trade works. American Economic Review 87 (3), 421–446.

Deardorff, A., 1974. Factor proportions and comparative advantage in the long-run: comment. Journal of Political Economy 82 (4), 829–833.

Dixit, A., Norman, V., 1980. The Theory of International Trade. Cambridge University Press, Cambridge, UK.

Feenstra, R., Hanson, G., 1999. The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990. Quarterly Journal of Economics August, 907–940.

Feenstra, R., Rose, A., 2000. Putting things in order: trade dynamics and product cycles. Review of Economics and Statistics 82 (3), 369–382.

Findlay, R., 1970. Factor proportions and comparative advantage in the long run. Journal of Political Economy 78 (1), 27–34.

Gandal, N., Hanson, G., Slaughter, M., 2000. Technology, trade, and adjustment to immigration in Israel. NBER Working Paper 7962.

Geweke, J., Marshall, R., Zarkin, G., 1986. Mobility indices in continuous time Markov chains. Econometrica 54, 1407–1423.

Griffith, R., Redding, S., Van Reenen, J., 2000. Mapping the two faces of R&D: productivity growth in a panel of OECD manufacturing industries. CEPR Discussion Paper 2457.

Grossman, G., Helpman, E., 1991. Innovation and Growth in the Global Economy. MIT Press, Cambridge, MA.

Hanson, H., Slaughter, M., 1999. The Rybczynski Theorem, factor-price equalisation, and immigration: evidence from US states. NBER Working Paper 7074.

Harrigan, J., 1995. Factor endowments and the international location of production: econometric evidence for the OECD, 1970–85. Journal of International Economics 39, 123–141.

Harrigan, J., 1997. Technology, factor supplies, and international specialisation: estimating the neoclassical model. American Economic Review 87 (4), 475–494.

Harrigan, J., 1999. Estimation of cross-country differences in industry production functions. Journal of International Economics 47 (2), 267–293.

Harrigan, J., Zakrajsek, E., 2000. Factor supplies and specialisation in the world economy. NBER Working Paper 7848.

Hinloopen, J., van Marrewijk, C., 1998. On the empirical distribution of revealed comparative advantage 1: shape and time. Paper presented at the CEPR European Research Workshop in International Trade. Erasmus University, mimeo.

Kim, S., 1995. Expansion of markets and the geographic distribution of economic activities: the tends in U.S. regional manufacturing structure, 1860–1987. Quarterly Journal of Economics 110 (4), 881–908.

Kohli, U., 1991. Technology, Duality and Foreign Trade. University of Michigan Press, Ann Arbor.

Krugman, P., 1987. The narrow moving band, the Dutch Disease and the competitive consequences of Mrs Thatcher: notes on trade in the presence of scale economies. Journal of Development Economics 27, 41–55.

Leamer, E., 1984. Sources of Comparative Advantage: Theories and Evidence. MIT Press.

Leamer, E., 1998. In search of Stolper–Samuelson linkages between international trade and lower wages. In: Collins, S. (Ed.), Imports, Exports, and the American Worker. Brookings Institution Press, Washington, DC, Chapter 4.

Lucas, R., 1988. On the mechanics of economic development. Journal of Monetary Economics 22, 3–22.
Machin, S., Van Reenen, J., 1998. Technology and changes in skill structure: evidence from seven OECD countries. Quarterly Journal of Economics November, 1215–1244.
Maskus, K., 1983. Evidence on shifts in the determinants of the structure of US manufacturing foreign trade, 1958–76. Review of Economics and Statistics 65, 415–422.
Nickell, S., Bell, B., 1996. Changes in the distribution of wages and unemployment in OECD countries. American Economic Review 86 (2), 302–308.
Nickell, S., Redding, S., Swaffield, J., 2000. Educational attainment, labour market institutions, and the structure of production. CEPR Discussion Paper, 3068.
Overman, H., Redding, S., Venables, A., 2001. The economic geography of trade, production, and income: a survey of empirics. In: Harrigan, J. (Ed.), Handbook of International Trade. Basil Blackwell, Oxford, forthcoming.
Proudman, J., Redding, S., 1998. Persistence and mobility in international trade. In: Proudman, J., Redding, S. (Eds.), Openness and Growth. Bank of England, London, Chapter 2.
Proudman, J., Redding, S., 2000. Evolving patterns of international trade. Review of International Economics 8 (3), 373–396.
Quah, D., 1993. Empirical cross-section dynamics in economic growth. European Economic Review 37, 426–434.
Quah, D., 1996a. Twin peaks: growth and convergence in models of distribution dynamics. Economic Journal 106, 1045–1055.
Quah, D., 1996b. Convergence empirics across economies with (some) capital mobility. Journal of Economic Growth 1, 95–124.
Quah, D., 1996c. Aggregate and regional disaggregate fluctuations. Empirical Economics 21, 137–159.
Quah, D., 1997. Empirics for economic growth and distribution: polarization, stratification, and convergence clubs. Journal of Economic Growth 2 (1), 27–59.
Redding, S., 1999a. Dynamic comparative advantage and the welfare effects of trade. Oxford Economic Papers 51, 15–39.
Redding, S., 1999b. The dynamics of international specialization. CEPR Discussion Paper 2287.
Shorrocks, A., 1978. The measurement of mobility. Econometrica 46, 1013–1024.
Stern, R., Maskus, K., 1981. Determinants of US foreign trade, 1958–76. Journal of International Economics 11 (2), 207–224.
Stolpe, M., 1994. Technology and empirical dynamics of specialization in open economies. Kiel Working Paper 637. Kiel Institute of World Economics, Germany.
Trefler, D., 1995. The case of the missing trade and other mysteries. American Economic Review 85 (5), 1029–1046.